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The Role of Cognitive Offloading in Mediating the Effects of Creativity, Artificial Intelligence, and Critical Thinking on Higher Order Thinking Skills

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Abstract

This study investigates the role of cognitive offloading in mediating the effects of creativity, artificial intelligence (AI), and critical thinking on Higher Order Thinking Skills (HOTS). A quantitative design using Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied. The respondents were undergraduate students from three universities in Indonesia (Universitas Lampung, Universitas Aisyah Pringsewu, and IIB Darmajaya). Using the Slovin formula with a 10% margin of error, 295 questionnaires were distributed, and 202 valid responses were obtained from students who reported frequent use of AI in academic activities. The findings indicate that creativity, AI, and critical thinking positively and significantly influence cognitive offloading. Critical thinking and cognitive offloading significantly affect HOTS, while creativity and AI do not show significant direct effects on HOTS. Cognitive offloading fully mediates the effects of creativity and AI on HOTS and partially mediates the effect of critical thinking on HOTS. The structural model explains 51.9% of the variance in HOTS ($R^2 = 0.519$). These results highlight that AI integration alone does not automatically enhance higher-order thinking; instead, structured cognitive regulation strategies—particularly cognitive offloading and critical thinking—are essential for optimizing AI-based learning in higher education.

Keywords: artificial intelligence, creativity, critical thinking, cognitive offloading, HOTS, SEM-PLS

1 Introduction

The rapid advancement of Artificial Intelligence (AI) has significantly transformed contemporary education through intelligent tutoring systems, adaptive learning platforms, and generative AI tools that support personalized instruction and automated feedback[1][2]. Empirical studies have begun to explore whether AI contributes to higher-order learning outcomes. For example[3]report that AI-supported systems can enhance problem-solving performance and adaptive reasoning, while[4] found that generative AI tools may assist students in analytical and creative tasks. However, these studies primarily measure outcome improvements rather than examining the cognitive processes that mediate such effects. Consequently, whether AI directly enhances Higher Order Thinking Skills (HOTS) remains inconclusive.

HOTS, encompassing analysis, evaluation, and creation within the revised Bloom's taxonomy[5] is widely recognized as a core 21st-century competency[6]. Although digital technologies may increase engagement[7], research consistently cautions that technology use does not automatically promote deep cognitive processing, particularly without metacognitive regulation[8]. Thus, improved engagement or performance does not necessarily indicate the development of higher-order thinking.

Most prior research on AI in education has emphasized direct relationships between AI usage and learning outcomes, often employing experimental or survey designs that focus on achievement gains, task efficiency, or user satisfaction[3],[4]. While valuable, such approaches tend to overlook the cognitive regulation mechanisms underlying technology-enhanced thinking. As[9] argue, understanding how learners allocate cognitive resources and regulate learning processes is essential for explaining complex learning outcomes in digital environments.

One relevant explanatory mechanism is cognitive offloading, defined as the strategic transfer of cognitive demands to external tools to manage limited working memory resources[10] Although

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cognitive offloading has been widely examined in cognitive psychology, its mediating role within AI-based learning contexts remains underexplored. Furthermore, few studies integrate creativity, AI usage, critical thinking, and cognitive offloading within a single structural framework to explain HOTS development.

Addressing these gaps, the present study proposes a Partial Least Squares Structural Equation Modeling (PLS-SEM) framework in which creativity, AI usage, and critical thinking function as predictors of HOTS through the mediating role of cognitive offloading [11]. Unlike previous research that primarily tests direct effects, this study explicitly models cognitive regulation as a structural mediator. The novelty lies in demonstrating that AI does not directly enhance HOTS; rather, its effectiveness depends on structured cognitive regulation mechanisms that transform AI interaction into higher-order cognitive development.

2 Literature Review

2.1. AI and Higher-Order Thinking

Artificial Intelligence (AI) has increasingly transformed educational environments through intelligent tutoring systems, adaptive learning platforms, and generative AI tools that personalize instruction and automate feedback processes [1],[2] Empirical studies report that AI-supported learning environments can enhance efficiency, accelerate feedback cycles, and scaffold student reasoning during complex tasks[3] In particular, adaptive AI systems have been associated with improvements in analytical reasoning and structured problem-solving[4] suggesting potential contributions to higher-order cognition.

However, the relationship between AI and higher-order thinking remains conceptually contested. While technological affordances may support performance outcomes, several scholars caution against equating technological integration with cognitive advancement. [8]argue that digital exposure alone does not inherently cultivate deep cognitive skills. Similarly,[12] emphasizes that technology should be understood as an instructional tool rather than an autonomous cognitive driver; its impact depends largely on pedagogical structure and learner agency.

Higher Order Thinking Skills (HOTS) encompassing analysis, evaluation, and creation [5]require intentional and structured cognitive engagement. These skills involve the regulation of mental processes, integration of information, and evaluative judgment beyond surface-level information processing. Therefore, although AI may provide scaffolding and external support, its contribution to HOTS likely depends on how learners regulate and distribute cognitive resources during interaction with technological systems. This suggests that examining internal cognitive mechanisms is essential to understanding the AI–HOTS relationship.

2.2. Cognitive Offloading as a Mediating Mechanism

Cognitive offloading refers to the deliberate transfer of cognitive tasks to external tools in order to manage limited working memory capacity[13] From the perspective of Cognitive Load Theory, learners possess finite cognitive resources; therefore, strategic management of cognitive load allows greater allocation of mental capacity toward higher-level reasoning and evaluative processes[14].

Empirical research demonstrates that cognitive offloading can enhance performance by freeing internal resources for complex analysis and problem-solving[15]. For example, when learners use external tools to organize information or generate preliminary ideas, they may conserve cognitive energy for evaluation and synthesis. However, scholars also warn that excessive or unregulated offloading may reduce internal elaboration and limit deep cognitive engagement[13]. In such cases, learners may rely on external outputs without critically processing the underlying reasoning.

This dual function positions cognitive offloading as both a potential enhancer and a potential constraint of higher-order thinking. In AI-mediated learning environments, tools such as generative AI frequently act as external memory supports, idea generators, and problem-solving assistants. Consequently, the impact of AI on HOTS may not be direct; rather, it may operate through the extent to which learners strategically externalize cognitive demands while maintaining reflective control. Modeling cognitive offloading as a mediator therefore provides a theoretically grounded explanation for the mixed findings in prior AI research.

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2.3. Creativity and Critical Thinking

Creativity and critical thinking represent foundational cognitive capacities associated with advanced intellectual performance. Creativity promotes originality, divergent thinking, and flexibility in idea generation[16]. Critical thinking, in contrast, emphasizes reflective judgment, evaluation of evidence, and reasoned decision-making[17]. Together, these constructs form core components of higher-order cognition.

Nevertheless, possessing creative or critical abilities does not automatically guarantee strong HOTS performance. Creative ideation without evaluative refinement may produce novel yet analytically weak outcomes. Similarly, critical thinking requires active cognitive regulation to be effectively enacted in authentic problem-solving contexts. The translation of these internal capacities into observable higher-order thinking performance depends on how individuals manage cognitive resources and structure reasoning processes.

Recent theoretical discussions highlight the metacognitive dimension of both creativity and critical thinking. Individuals with stronger internal cognitive capacities may be more capable of strategically regulating their interaction with external tools. In AI-supported learning contexts, such learners may use AI not merely as a shortcut but as a scaffold to enhance reflective reasoning. Thus, creativity and critical thinking may influence HOTS both directly and indirectly through their effect on cognitive offloading strategies.

2.4. Conceptual Integration and Hypotheses Development

The preceding literature yields several important theoretical implications. First, AI does not inherently generate higher-order cognition; its educational impact depends on learner regulation and cognitive strategy use. Second, cognitive offloading represents a dual mechanism that can either facilitate or hinder deep processing depending on its strategic implementation. Third, internal cognitive capacities such as creativity and critical thinking likely shape how learners engage with AI and regulate external cognitive supports.

Despite these insights, prior studies have rarely integrated these constructs within a unified structural framework. Much of the existing research examines direct effects (e.g., AI → learning outcomes) without modeling mediating cognitive processes. Consequently, the structural interplay among AI usage, individual cognitive traits, cognitive offloading, and HOTS remains insufficiently explored.

To address this theoretical and empirical gap, the present study proposes a PLS-SEM model in which creativity, AI usage, and critical thinking function as predictors of HOTS through the mediating role of cognitive offloading. This integrative approach moves beyond technological determinism and positions cognitive regulation as the central explanatory mechanism linking AI and higher-order thinking.

Direct Effects on Cognitive Offloading
H1: Creativity positively and significantly influences cognitive offloading.
H2: Artificial Intelligence positively and significantly influences cognitive offloading.
H3: Critical thinking positively and significantly influences cognitive offloading.
Direct Effects on HOTS
H4: Cognitive offloading positively and significantly influences HOTS.
H5: Creativity positively and significantly influences HOTS.
H6: Artificial Intelligence positively and significantly influences HOTS.
H7: Critical thinking positively and significantly influences HOTS.
Mediating Effects
H8: Cognitive offloading mediates the relationship between creativity and HOTS.
H9: Cognitive offloading mediates the relationship between AI and HOTS.
H10: Cognitive offloading mediates the relationship between critical thinking and HOTS.

3 Research Method

3.1. Research Design

This study employed a quantitative approach with an explanatory research design to examine the causal relationships among creativity, Artificial Intelligence (AI) usage, critical thinking, cognitive offloading, and Higher Order Thinking Skills (HOTS). The explanatory design was selected because the study aims to analyze both direct and indirect (mediated) effects within a proposed structural framework. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS software. The PLS-SEM approach was chosen based on several methodological considerations: The proposed model is relatively complex, involving multiple latent constructs and mediating relationships, The study is prediction-oriented and aims to test structural relationships rather than confirm a well-established theory, The final sample size (n = 202) is moderate, PLS-SEM does not require strict multivariate normality assumptions and is suitable for exploratory and predictive modeling[11]Thus, PLS-SEM is considered appropriate for testing the structural relationships in AI-supported learning contexts.

3.2. Population and Sample

3.2.1 Population

The population of this study consisted of undergraduate students enrolled in three higher education institutions in Lampung Province, Indonesia: Universitas Lampung (approximately 45,951 students), Universitas Aisyah Pringsewu (approximately 4,842 students), Institut Informatika dan Bisnis (IIB) Darmajaya (approximately 2,807 students). These institutions were selected because they represent public and private universities with diverse academic backgrounds and increasing integration of AI-based tools in learning activities.

3.2.2. Sampling Technique and Recruitment Procedure

This study employed purposive sampling to ensure that respondents met specific criteria relevant to the research objectives. The inclusion criteria were: The respondent is an undergraduate student actively enrolled at one of the three universities, The respondent frequently uses AI-based tools (e.g., ChatGPT or other AI applications) for academic purposes, The respondent has experience with technology-enhanced learning, The respondent voluntarily completed the questionnaire.

The initial target sample size was determined using the Slovin formula with a 10% margin of error. Based on this calculation, the minimum required respondents were: Universitas Lampung: 100 respondents, Universitas Aisyah Pringsewu: 98 respondents, IIB Darmajaya: 97 respondents. Thus, 295 questionnaires were distributed proportionally across the three universities using an online survey platform. The survey link was disseminated through student communication channels, including academic groups and institutional networks.

To ensure data relevance, a screening question was included at the beginning of the questionnaire:
"Do you frequently use AI tools for academic activities?" Respondents who answered "Yes" were allowed to proceed with the full questionnaire. Those who answered "No" were automatically excluded from further participation.

Out of 295 distributed questionnaires: 202 respondents met the screening criteria and completed the questionnaire in full, 93 respondents did not proceed because they reported not frequently using AI tools.Therefore, the final sample consisted of 202 undergraduate students who actively use AI in academic contexts.

3.2.3. Sample Adequacy

Methodologically, the final sample size satisfies the minimum requirement for PLS-SEM based on the 10-times rule [11]which recommends that the sample size be at least ten times the maximum number of structural paths directed at a construct. In this model, the HOTS construct receives three direct paths; thus, the minimum required sample size (10 × 3 = 30) has been substantially exceeded.

Accordingly, the sample size is considered adequate for reliable model estimation and hypothesis testing.

3.3 Research Instrument

Data were collected using a structured self-administered questionnaire measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). All constructs in this study were operationalized as reflective constructs, meaning that the indicators are assumed to reflect the underlying latent variable. The questionnaire items were developed based on established theoretical definitions of each construct and adapted to the context of

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AI-supported learning. Below are examples of measurement items for each construct,as shown in Table 1.

Table 1. Measurement instruments

Construct	Code	Measurement Item	Scale
Artificial Intelligence (AI)	Ai1	I frequently use AI-based tools to search for information or solve academic problems.	1–5 Likert
	Ai2	I feel comfortable using AI tools in making decisions	1–5 Likert
	Ai3	Using AI tools helps me find information more quickly.	1–5 Likert
	Ai4	I have confidence in the answers provided by AI systems.	1–5 Likert
Critical Thinking (BK)	BK1	I critically evaluate information sources or recommendations, including those obtained from AI.	1–5 Likert
	BK2	I verify information by comparing multiple sources when researching a topic.	1–5 Likert
	BK3	When making decisions, I evaluate possible biases in my thinking.	1–5 Likert
	BK4	When receiving information from AI, I consider possible hidden motives behind it.	1–5 Likert
	BK5	I consider the credibility of sources when receiving information from AI tools.	1–5 Likert
	BK6	I review various sources before concluding based on AI recommendations.	1–5 Likert
	BK7	I reconsider the reasoning behind information provided by AI systems.	1–5 Likert
Creativity (KR)	KR1	I use AI to discover new ideas I had not previously considered.	1–5 Likert
	KR2	When using AI, I find various alternative solutions to a problem.	1–5 Likert
	KR3	With AI assistance, I can develop initial ideas into deeper solutions.	1–5 Likert
	KR4	I use AI to imagine ideas that have never existed before	1–5 Likert
Cognitive Offloading (CO)	CO1	I frequently use search engines to obtain information.	1–5 Likert
	CO2	Compared to the past, technology allows me to find information more quickly and easily.	1–5 Likert
	CO3	I often use smartphones or digital devices to remind me of tasks or information.	1–5 Likert
Higher Order Thinking Skills (HOTS)	HOTS1	I can analyze the structure of arguments and understand logical flow in a text.	1–5 Likert
	HOTS2	I can distinguish relevant from less important information in a text.	1–5 Likert
	HOTS3	I can evaluate different ideas recommended by AI and choose the most appropriate one.	1–5 Likert
	HOTS4	I can create new solutions by integrating AI to solve problems.	1–5 Likert

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Measurement Model Refinement

During the initial evaluation of the measurement model, indicators with outer loadings below 0.70 were removed to ensure convergent validity. Two indicators (Ai2 and KR4) were excluded based on this criterion. After refinement, all retained indicators demonstrated satisfactory outer loadings, Average Variance Extracted (AVE > 0.50), and Composite Reliability (> 0.70), indicating adequate validity and reliability.

3.4 Data Analysis Technique

Data analysis was conducted using SmartPLS in two main stages: evaluation of the measurement model (outer model) and evaluation of the structural model (inner model).

3.4.1 Measurement Model Evaluation (Outer Model)

The outer model was assessed to examine construct validity and reliability.

1. Convergent Validity

   Convergent validity was evaluated using: Outer loadings (> 0.70), Average Variance Extracted (AVE > 0.50) The AVE values for each construct were: AI = 0.673, Critical Thinking (BK) = 0.595, CO = 0.661, HOTS = 0.678, Creativity (KR) = 0.651 All AVE values exceeded 0.50, indicating satisfactory convergent validity.
2. Discriminant Validity

   Discriminant validity was assessed using Cross loadings and The Fornell–Larcker criterion The square root of AVE for each construct was greater than its correlations with other constructs, indicating adequate discriminant validity
3. Construct Reliability

   Construct reliability was evaluated using Cronbach's Alpha (> 0.70), Composite Reliability (> 0.70). All constructs exceeded the recommended thresholds and were therefore considered reliable.

3.4.2. Structural Model Evaluation (Inner Model)

The inner model evaluation aimed to assess the strength of the relationships among latent constructs.

1. Coefficient of Determination (R^2)

   The R^2 values indicate the proportion of variance in endogenous constructs explained by exogenous constructs: CO = 0.348, HOTS = 0.519. These values suggest moderate to substantial predictive accuracy of the model.
2. Effect Size (f^2)

   Effect size (f^2) was calculated to determine the contribution of each exogenous variable to the endogenous variables. The interpretation criteria were: 0.02 = small, 0.15 = medium, 0.35 = large
3. Predictive Relevance (Q^2)

   The Q^2 value of 0.433 (> 0) indicates that the model possesses strong predictive relevance.
4. Model Fit

   Model fit was evaluated using several indices: SRMR = 0.086 (< 0.10), GoF = 0.525 (strong), NFI = 0.744. Based on these indicators, the structural model demonstrates an acceptable overall fit.

3.5. Hypothesis Testing and Mediation Analysis

Hypothesis testing was conducted using a bootstrapping procedure with 5,000 subsamples to obtain t-statistics and p-values. The significance criteria were $p < 0.05$ indicates a significant effect, t-statistics > 1.96 indicates significance at $\alpha = 0.05$. Mediation

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analysis was performed by comparing direct and indirect effects using bootstrapped confidence intervals. Mediation was categorized as **Full mediation**, when the direct effect is not significant but the indirect effect is significant, **Partial mediation**, when both direct and indirect effects are significant. This procedure follows the recommended mediation analysis approach in PLS-SEM[18].

4 Results and Analysis

Introduction to Research Results

This section presents the empirical findings of the research model using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The evaluation was conducted systematically through two main stages: assessment of the measurement model (outer model) and evaluation of the structural model (inner model).

The first stage aimed to ensure that the latent constructs met the required validity and reliability criteria. Once the measurement model was deemed adequate, the analysis proceeded to the structural model to examine the strength of the relationships among variables and to evaluate the mediating role of cognitive offloading in explaining Higher Order Thinking Skills (HOTS).

4.1. Measurement Model Evaluation (Outer Model)

4.1.1. Convergent Validity

Convergent validity was assessed using outer loadings and Average Variance Extracted (AVE).

a. Outer Loadings

   In the initial analysis, two indicators had outer loading values below the recommended threshold of 0.70, namely Ai2 (0.694) and KR4 (0.682). Since these values did not meet the minimum requirement, both indicators were removed from the model.

   After eliminating these indicators, all remaining items demonstrated outer loading values above 0.70, indicating that each indicator adequately reflects its respective latent construct. This suggests that the items have strong explanatory power in measuring their corresponding variables.

b. Average Variance Extracted (AVE)

   The AVE value for each construct is AI = 0.673, Critical Thinking (BK) = 0.595, Cognitive Offloading (CO) = 0.661, HOTS = 0.678, Creativity (KR) = 0.651

All AVE values exceed the threshold of 0.50, indicating satisfactory convergent validity. This means that more than 50% of the variance in the indicators is explained by their respective latent constructs.

4.1.2. Discriminant Validity

Discriminant validity was examined using cross loadings, the Fornell–Larcker criterion, and latent variable correlations.

a. Cross Loadings

   The cross loading results indicate that each indicator loads highest on its intended construct compared to other constructs. This confirms that the indicators demonstrate adequate discriminant capability and that there is no significant overlap between constructs.

b. Fornell–Larcker Criterion

   The square root of AVE for each construct was greater than its correlations with other constructs.For example:

   $\sqrt{}$ AVE of HOTS = 0.823, which is higher than its correlations with other constructs.

$\sqrt{}$ AVE of CO = 0.813, which exceeds its correlations with AI, BK, and KR.
These findings confirm that discriminant validity is established.

c. Latent Variable Correlations
The highest correlation was observed between BK and HOTS (0.654), indicating a substantively strong relationship. However, this value remains lower than the square root of AVE for both constructs, suggesting that multicollinearity among latent variables is not a concern.

4.1.3. Reliability Assessment

Construct reliability was evaluated using Cronbach's Alpha and Composite Reliability.

a. Cronbach's Alpha
BK = 0.887, HOTS = 0.840, AI = 0.757, CO = 0.743, KR = 0.733
All values exceed the recommended threshold of 0.70, indicating acceptable internal consistency.

b. Composite Reliability
BK = 0.911, HOTS = 0.893, AI = 0.860, CO = 0.854, KR = 0.848
All composite reliability values are above 0.70, confirming strong internal consistency across constructs

4.1.4. Model Fit

Model fit evaluation shows the following results: SRMR = 0.086 (< 0.10), indicating acceptable model fit, GoF = 0.525, categorized as strong, NFI = 0.744, approaching the ideal value of 1, Q^2 = 0.433 (> 0), indicating strong predictive relevance.

Although the Chi-square value does not meet conventional covariance-based SEM criteria, this index is not the primary focus in PLS-SEM, as the approach is variance-based rather than covariance-based. Overall, the measurement model is considered adequate and suitable for structural model evaluation.

4.2. Structural Model Evaluation (Inner Model)

4.2.1. Coefficient of Determination (R^2)

The R^2 values are as follows R^2 for CO = 0.348, R^2 for HOTS = 0.519

The R^2 value of 0.519 indicates that 51.9% of the variance in HOTS is explained by creativity, AI, critical thinking, and cognitive offloading. In social science research, this value is considered moderate to substantial.

4.2.2. Path Coefficients and Significance Testing

Bootstrapping results reveal the following effects on cognitive offloading:

AI → CO (β = 0.181; p = 0.017) significant, BK → CO (β = 0.222; p = 0.002) significant, KR → CO (β = 0.352; p = 0.000) significant

These findings indicate that all three exogenous variables significantly increase cognitive offloading.

Regarding the effects on HOTS:

BK → HOTS (β = 0.499; p = 0.000) significant, CO → HOTS (β = 0.289; p = 0.000) significant, AI → HOTS (β = 0.087; p = 0.094) not significant, KR → HOTS (β = 0.008; p = 0.458) not significant

These results demonstrate that critical thinking is the strongest predictor of HOTS in the model.

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4.2.3. Effect Size (f^2)

The effect size analysis indicates that:
BK → HOTS has a large effect, CO → HOTS has a medium effect, AI → HOTS has a small effect, KR → HOTS has a very small effect.
This further confirms that critical thinking contributes most substantially to the improvement of HOTS.

4.3. Mediation Analysis

a. AI → HOTS
   The direct effect is not significant, while the indirect effect through CO is significant. Therefore, full mediation occurs.
b. KR → HOTS
   The direct effect is not significant, but the indirect effect through CO is significant. This indicates full mediation.
c. BK → HOTS
   Both the direct and indirect effects are significant. Thus, partial mediation is observed.

Main Substantive Interpretation

The findings reveal that Artificial Intelligence (AI) does not exert a significant direct influence on Higher Order Thinking Skills (HOTS). Likewise, creativity does not directly enhance HOTS within the proposed structural model. These results challenge the common assumption that exposure to advanced technologies or creative capacity alone automatically leads to higher-level cognitive development.

Instead, cognitive offloading emerges as a pivotal mediating mechanism that explains how AI and creativity contribute to HOTS. This suggests that the impact of AI and creative potential on higher-order thinking is not inherent but depends on how individuals strategically regulate and distribute their cognitive processes. In this context, cognitive offloading functions as a regulatory bridge that transforms technological interaction and creative capacity into meaningful cognitive advancement.

Moreover, critical thinking appears as the strongest determinant of HOTS, highlighting the central role of evaluative and reflective reasoning in higher-order cognitive performance. This finding reinforces the argument that technological tools do not independently drive cognitive sophistication. Rather, it is the individual's metacognitive and regulatory capacity—particularly the strategic use of cognitive offloading—that determines whether AI can meaningfully enhance higher-order thinking skills.

Overall, these findings reposition technology from being a primary driver of cognitive growth to being a supportive instrument whose effectiveness depends on the learner's cognitive regulation strategies.

This study empirically examines how cognitive offloading functions as a mediating mechanism in the relationship between creativity, Artificial Intelligence (AI), critical thinking, and Higher Order Thinking Skills (HOTS). The findings not only reveal statistical relationships among variables but also offer a reconceptualization of the role of technology in cognitive development.

4.4. AI Does Not Inherently Enhance HOTS

The results indicate that AI does not have a significant direct effect on HOTS. This finding challenges the dominant narrative in digital education discourse, which often assumes that the integration of technology automatically improves higher-order thinking abilities.

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These results suggest that technology, including AI, is not an autonomous cognitive agent. Rather, AI functions as an external tool whose potential depends largely on how users regulate and manage their interaction with it. Without adequate cognitive regulation, AI risks becoming merely a substitute for information retrieval rather than a facilitator of cognitive transformation.

From the perspective of Cognitive Load Theory, technology is effective only when it helps individuals allocate cognitive resources efficiently. Therefore, AI does not inherently enhance HOTS; what ultimately determines its effectiveness is the individual's cognitive regulation strategy.

4.5. Creativity Does Not Automatically Correlate with HOTS

The finding that creativity does not directly influence HOTS indicates that the ability to generate ideas does not necessarily translate into analytical and evaluative competence. Creativity without cognitive regulation may foster originality, but it does not automatically result in cognitive complexity.

This suggests that creative potential requires mechanisms for processing and distributing cognitive load in order to evolve into higher-order thinking skills. In other words, creativity must be mediated by cognitive strategies to meaningfully contribute to HOTS development.

4.6. Critical Thinking as the Primary Cognitive Foundation

Critical thinking emerges as the variable with the strongest direct influence on HOTS ($\beta = 0.499$). This underscores the central role of evaluative and reflective reasoning in higher-level cognitive performance.

The findings reinforce the argument that, despite rapid technological advancement, the quality of thinking remains fundamentally determined by individuals' internal cognitive capacities. Technology may expand access to information, but the ability to evaluate, filter, and interpret information depends on critical thinking skills.

4.7. Cognitive Offloading as a Transformational Mechanism

The primary contribution of this study lies in demonstrating that cognitive offloading operates as a transformational mechanism. The results indicate that: The relationship between AI and HOTS is fully mediated by cognitive offloading, The relationship between creativity and HOTS is fully mediated by cognitive offloading, The relationship between critical thinking and HOTS is partially mediated by cognitive offloading.

These findings suggest that the effects of AI and creativity on HOTS do not occur directly but rather through the distribution and management of cognitive load.

In this context, cognitive offloading functions as a regulatory bridge that enables individuals to utilize external resources in order to strengthen internal cognitive processes. Consequently, technology is not the primary determinant of HOTS; instead, it serves as a medium whose effectiveness depends on the user's cognitive regulation strategies.

4.8. Repositioning the Role of Technology in Education

Conceptually, this study repositions the role of technology in education. AI is not the main driver of cognitive development but rather a supportive instrument that requires metacognitive capacity to contribute effectively.

These findings shift the focus from "technology-driven learning" toward "cognition-driven technology use." In other words, what matters is not the sophistication of the technology itself, but how individuals integrate it into their cognitive processes.

4.9. Theoretical and Practical Implications

From a theoretical perspective, this study expands the understanding of cognitive offloading theory within the context of AI-based learning and provides empirical evidence regarding mediation mechanisms between technology use and HOTS. Practically, the

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findings suggest that: AI integration should be accompanied by cognitive and metacognitive regulation training, Curricula should emphasize reflective and strategic technology use, Strengthening critical thinking must remain a central priority in 21st-century education.

Table 2. Summary of measurement model (outer model) evaluation

Parameter	Criteria	Result	Interpretation
Loading Factor	> 0.70	0.723 – 0.887	Valid
AVE	> 0.50	0.595 – 0.678	Valid
Cronbach's Alpha	> 0.70	0.733 – 0.887	Reliable
Composite Reliability	> 0.70	0.848 – 0.911	Reliable
Fornell–Larcker	√AVE > correlations	Fulfilled	Valid
SRMR	< 0.10	0.086	Fit
GoF	> 0.36	0.525	Strong Fit

Table 2 presents the summary of the measurement model (outer model) evaluation. The results indicate that all constructs meet the required validity and reliability criteria. The loading factor values range from 0.723 to 0.887, exceeding the recommended threshold of 0.70, which confirms that all indicators adequately represent their respective latent constructs. Furthermore, the Average Variance Extracted (AVE) values range from 0.595 to 0.678, surpassing the minimum criterion of 0.50. This demonstrates satisfactory convergent validity, indicating that more than 50% of the variance in the indicators is explained by their corresponding constructs.

In terms of reliability, both Cronbach's Alpha (0.733–0.887) and Composite Reliability (0.848–0.911) exceed the recommended threshold of 0.70, confirming strong internal consistency across all constructs. Discriminant validity is also established, as the Fornell–Larcker criterion is fulfilled, with the square root of AVE for each construct being greater than its correlations with other constructs.

Additionally, the model fit indices indicate acceptable overall model adequacy. The SRMR value of 0.086 is below the recommended threshold of 0.10, suggesting a good model fit. The Goodness of Fit (GoF) value of 0.525 exceeds 0.36, indicating a strong model fit. Collectively, these results demonstrate that the measurement model is valid, reliable, and suitable for subsequent structural model analysis.

Table 3. Summary of structural model (inner model) evaluation

Path	Coefficient (β)	t-value	p-value	Interpretation
AI → CO	0.181	2.129	0.017	Significant
BK → CO	0.222	2.829	0.002	Significant
KR → CO	0.352	4.982	0.000	Significant
CO → HOTS	0.289	4.795	0.000	Significant

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BK → HOTS	0.499	9.287	0.000	Significant
AI → HOTS	0.087	1.314	0.094	Not significant
KR → HOTS	0.008	0.106	0.458	Not significant

Table 3 presents the results of the structural model (inner model) evaluation obtained through the bootstrapping procedure. The findings indicate that several structural paths are statistically significant, while others are not.

Regarding the effects on cognitive offloading (CO), all three exogenous variables demonstrate positive and significant relationships. Artificial Intelligence (AI) significantly influences CO ($\beta = 0.181$; $t = 2.129$; $p = 0.017$). Critical Thinking (BK) also shows a significant effect on CO ($\beta = 0.222$; $t = 2.829$; $p = 0.002$). Creativity (KR) exhibits the strongest influence on CO ($\beta = 0.352$; $t = 4.982$; $p = 0.000$). These results suggest that increased AI usage, higher creativity, and stronger critical thinking skills significantly promote cognitive offloading.

With respect to HOTS, Critical Thinking (BK) demonstrates the strongest and most significant effect ($\beta = 0.499$; $t = 9.287$; $p = 0.000$), followed by Cognitive Offloading ($\beta = 0.289$; $t = 4.795$; $p = 0.000$). This indicates that critical thinking is the primary predictor of HOTS, while cognitive offloading also plays a significant role in enhancing higher-order thinking skills.

In contrast, Artificial Intelligence (AI) does not have a significant direct effect on HOTS ($\beta = 0.087$; $t = 1.314$; $p = 0.094$). Similarly, Creativity (KR) does not significantly influence HOTS ($\beta = 0.008$; $t = 0.106$; $p = 0.458$). These findings imply that the effects of AI and creativity on HOTS occur indirectly through the mediating mechanism of cognitive offloading.

Overall, the structural model results highlight the central roles of critical thinking and cognitive offloading in enhancing HOTS, while AI and creativity contribute indirectly through cognitive regulation processes.

Table 4. Coefficient of determination (R^2)

Endogenous Variable	**R^2**	**Interpretation**
Cognitive Offloading	0.348	Moderate
HOTS	0.519	Moderate–Strong

Table 4 presents the coefficient of determination (R^2) values for the endogenous variables in the research model. The R^2 value for Cognitive Offloading is 0.348, indicating that 34.8% of the variance in this construct is explained by the exogenous variables, namely Artificial Intelligence (AI), creativity, and critical thinking. This value falls within the moderate category, suggesting that the model demonstrates an adequate explanatory power in predicting cognitive offloading.

Meanwhile, the R^2 value for HOTS is 0.519, meaning that 51.9% of the variance in Higher Order Thinking Skills is explained by creativity, AI, critical thinking, and cognitive offloading. In social science and educational research, this value can be considered moderate

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to substantial. This indicates that the model possesses strong explanatory capability in accounting for the factors influencing HOTS.

Overall, these results suggest that the structural model exhibits good predictive power in explaining the endogenous constructs under investigation.

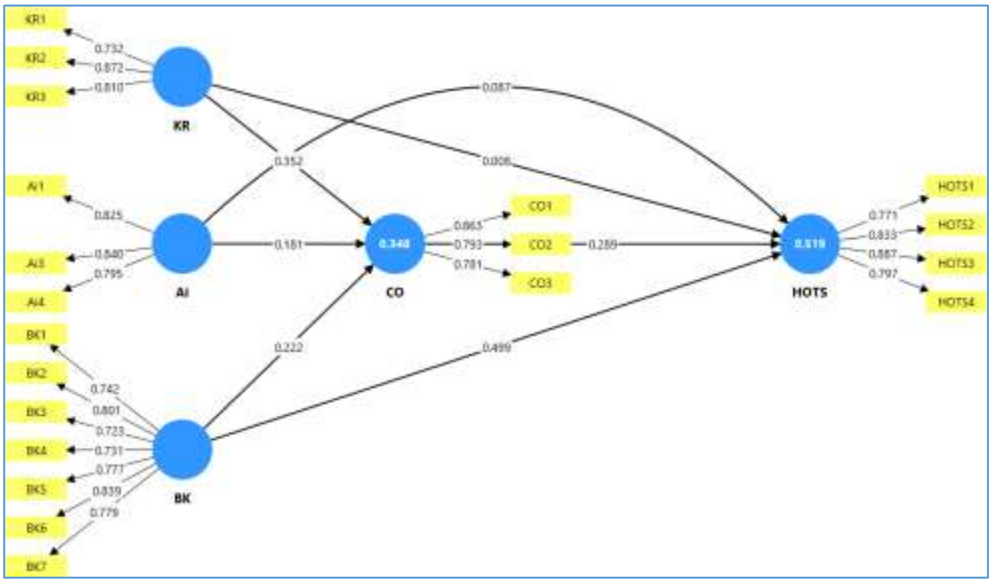

Figure 1. Structural equation modeling (sem) structural model diagram based on PLS (inner model PLS-SEM).

Figure 1 above shows that the structural model estimated using the PLS-SEM approach reveals relationship patterns that are not only statistically significant but also conceptually meaningful. Creativity (KR), Artificial Intelligence (AI), and Critical Thinking (BK) are positioned as predictor variables influencing Cognitive Offloading (CO), which subsequently contributes to Higher Order Thinking Skills (HOTS). All indicators demonstrate loading factors above 0.70, indicating that the constructs are measured consistently and possess adequate convergent validity. Therefore, the interpretation of the structural relationships can be conducted with a high level of confidence. Structurally, creativity ($\beta = 0.352$), AI ($\beta = 0.181$), and critical thinking ($\beta = 0.222$) positively influence cognitive offloading. These findings suggest that individuals with higher creative capacity, greater exposure to AI, and stronger critical thinking skills are more likely to actively distribute their cognitive load to external resources. However, the relationship pattern with respect to HOTS presents a more complex dynamic. Critical thinking emerges as the most dominant predictor ($\beta = 0.499$), reinforcing that evaluative and reflective abilities remain the primary foundation of higher-order thinking. Cognitive offloading also contributes significantly ($\beta = 0.289$), indicating that cognitive regulation strategies play an important role in strengthening HOTS. In contrast, the direct effects of AI ($\beta = 0.087$) and creativity ($\beta = 0.008$) on HOTS are not significant. This pattern indicates that technology and creative potential do not automatically transform thinking into higher cognitive complexity. Their influence depends on the cognitive mechanisms that mediate this process. The R^2 value of 0.519 for HOTS indicates that more than half of the variance in higher-order thinking skills is explained by the model. This figure confirms that the combination of cognitive regulation and internal cognitive capacity possesses substantial explanatory power. Overall, the model conveys a strong conceptual message: the improvement of HOTS is not merely the result of technology use or individual creativity, but rather depends on how individuals manage and integrate both within their cognitive processes through cognitive offloading. Accordingly, these findings open a broader discussion regarding the repositioning of technology's role in modern learning environments.

5 Conclusion

This study confirms that cognitive offloading plays a central mediating role in explaining how creativity, Artificial Intelligence (AI), and critical thinking influence Higher Order Thinking Skills (HOTS). The findings reveal that while creativity, AI usage, and critical thinking significantly increase students' engagement in cognitive offloading, only critical thinking demonstrates a direct effect on HOTS. AI and creativity influence HOTS indirectly through cognitive offloading, indicating full mediation, whereas critical thinking exhibits partial mediation. The model explains 51.9% of the variance in HOTS, which represents a moderate-to-strong explanatory power in social science research and suggests that the combination of internal cognitive capacities and cognitive regulation strategies substantially contributes to higher-order thinking development. Conceptually, these results reposition AI not as a direct driver of cognitive advancement but as a supportive instrument whose effectiveness depends on structured cognitive regulation. Practically, the findings imply that lecturers and instructional designers should integrate AI use with explicit metacognitive guidance and critical thinking training rather than relying solely on technological adoption. Policymakers in higher education should also emphasize AI literacy and cognitive regulation strategies within curriculum development to ensure meaningful learning outcomes. Nevertheless, this study has several limitations: it employed a cross-sectional design, relied on self-reported questionnaire data, and focused on undergraduate students from three universities in one Indonesian province, which may limit causal inference and generalizability. Future research is therefore encouraged to employ longitudinal and experimental designs, incorporate additional variables such as self-regulated learning or AI literacy, and test the model across diverse institutional and educational contexts. Overall, this study underscores the importance of shifting AI-based education from technology-centered implementation toward cognition-centered regulation as the foundation for developing higher-order thinking skills.

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