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The Bright and Dark Sides of AI Dependency on Students’ Critical Thinking: The Roles of Cognitive Fatigue and Engagement

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Abstract

Background/ problem: The rise of artificial intelligence (AI) use in education has sparked debate about its potential association with students’ critical thinking, while existing studies have reported inconsistent findings.

Objective/ purpose: This study examined how AI dependency affects students’ critical thinking disposition through the mediating roles of cognitive fatigue and engagement.

Design and Methodology: A cross-sectional survey was conducted among 639 university students in Java, Indonesia, using convenience sampling design. Data were collected through an online questionnaire and analyzed using partial least squares structural equation modeling (SEM-PLS).

Results: The findings show that AI dependency does not directly affect students’ critical thinking disposition ($\beta = .05, p = .31$). Instead, cognitive fatigue ($\beta = -.60, p = .00$) and engagement ($\beta = .36, p = .00$) significantly mediate the relationship in contrasting ways. On one hand, AI dependency increases cognitive fatigue, which subsequently weakens students’ critical thinking disposition. On the other hand, AI dependency promotes engagement, which in turn strengthens critical thinking disposition.

Conclusion and Implications: These findings suggest that AI dependency influence students’ critical thinking disposition indirectly through contrasting cognitive and behavioral pathways. From a behavioral-science perspective, modifiable student–AI interaction behaviors shape these outcomes. Educators should promote reflective AI engagement, require independent verification of AI-generated outputs, and design learning activities that maintain students’ responsibility for reasoning and decision-making. Strategies that limit cognitive offloading, uncritical acceptance of AI outputs, and excessive dependency help prevent cognitive fatigue and support students’ critical thinking disposition.

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The rapid development in artificial intelligence (AI) has been transforming all sectors, including education. One of the most popular AI tools among students is ChatGPT by OpenAI, which can understand conversational context, offer instant feedback, answer follow-up questions, and brainstorm ideas (Rozaimee & Mumin, 2025; Suriano et al., 2025). These AI capabilities enable students to delegate everyday academic tasks, such as completing schoolwork, academic writing, and problem-solving, particularly in higher education (Suriano et al., 2025; Tian & Zhang, 2025).

Nevertheless, the conveniences AI offers in assisting students have raised significant concerns, particularly about students’ cognitive development. On one hand, many scholars have argued that the use

of AI negatively affects students' critical thinking (Tian & Zhang, 2025; Venugopal & Vakamullu, 2025). However, other studies also find that students who use AI effectively tend to demonstrate a strong critical thinking disposition (Rudolph et al., 2023; Sanchez-Lopez et al., 2025; Suriano et al., 2025). Therefore, the impact of AI dependency on students' critical thinking disposition has not yet been conclusively determined and needs to be addressed in the current study.

The existing literature has largely examined whether AI dependency is positively or negatively associated with critical thinking, but it has paid comparatively less attention to what happens between the antecedent and the cognitive outcome. In particular, prior studies have not sufficiently explained how excessive reliance on AI may simultaneously alter students' available cognitive resources and their active involvement in learning. Consequently, the unresolved issue is not simply whether AI dependency improves or reduces critical thinking, but which psychological processes translate dependency into different cognitive consequences. This process-oriented gap is important because a single direct-effect model cannot explain why similar levels of AI dependency could produce either cognitive impairment or cognitive support.

The present study addresses this gap by examining two theoretically distinct mechanisms: cognitive fatigue and engagement. These mechanisms were selected because they represent complementary consequences of how limited cognitive resources are allocated during AI-supported learning. Cognitive fatigue represents a negative pathway through which prolonged or demanding interaction with AI could deplete attention, mental energy, and cognitive control, thereby reducing students' capacity for critical evaluation (Kotnik et al., 2024; Tian & Zhang, 2025). Under this condition, students are more likely to engage in cognitive offloading by relying on AI to generate answers or solve problems rather than engaging in independent reasoning (Skulmowski, 2023; Tian & Zhang, 2025), thereby reducing critical thinking disposition. In contrast, engagement represents a positive pathway through which students actively interact with AI by exploring alternatives, asking follow-up questions, evaluating outputs, and refining their own ideas (Palarimath et al., 2024; Suntharalingam, 2026). Other mechanisms, such as AI literacy, self-regulated learning, or automation bias, also plausibly explain the relationship between AI dependency and critical thinking. However, these constructs primarily capture students' competencies, regulatory strategies, or cognitive biases. Cognitive fatigue and engagement are more directly connected to the immediate allocation and availability of cognitive resources during AI-supported academic tasks, making them particularly well suited to explaining why AI dependency may produce contrasting consequences for critical thinking.

The cognitive load theory (CLT) provides an appropriate theoretical framework for integrating these two apparently opposing pathways. Cognitive load theory assumes that working memory has limited capacity and that learning depends on how available cognitive resources are allocated during task performance (Sweller, 1988). Accordingly, AI-supported learning can have different cognitive consequences depending on how students interact with AI: reliance on AI can lead to cognitive fatigue as information-processing demands accumulate, whereas active engagement allows students to redirect available cognitive resources toward higher-order activities such as questioning, evaluation, and reflection.

This issue is particularly relevant in higher education, where students routinely engage in cognitively demanding activities requiring independent reasoning, information evaluation, argument construction, and problem-solving. Evidence concerning these processes remains limited in the Indonesian higher-education context. The present study therefore focuses on university students in Java, Indonesia, to provide contextual evidence on whether the proposed dual-pathway relationship is also observed in this setting.

Accordingly, this study aims to examine the relationship between AI dependency and students' critical thinking disposition through two contrasting pathways: cognitive fatigue as a negative pathway and engagement as a positive pathway. By examining these pathways simultaneously, the study seeks to clarify why AI dependency is associated with different patterns of students' critical thinking disposition.

Literature Review

This section reviews the theoretical and empirical foundations of the proposed dual-pathway model. It first discusses the cognitive load theory (CLT) as the theoretical basis for understanding how AI dependency can alter the allocation of cognitive resources. It then examines the relationship between AI dependency and critical thinking disposition, followed by the proposed roles of cognitive fatigue and engagement as two contrasting pathways. Finally, the literature is integrated into the conceptual framework and hypotheses.

Cognitive Load Theory

The widespread adoption of AI across sectors, particularly in education, is inevitable. AI offers many advantages for students, such as providing quick access to real-time information, helping complete academic tasks, and facilitating collaborative brainstorming sessions for innovative ideas (Suriano et al., 2025; Tian & Zhang, 2025). However, the increasing reliance on AI has also raised concerns about its implications for students' cognitive development, particularly their critical thinking disposition. These effects depend on how students allocate cognitive resources when interacting with AI.

The cognitive load theory (CLT) assumes that working memory has limited capacity and that learning depends on how cognitive resources are allocated during task performance (Sweller, 1988). When academic tasks impose substantial demands, students can use cognitive offloading, defined as the use of external resources to reduce or redistribute cognitive demands (Risko & Gilbert, 2016). In AI-supported learning, students can offload information retrieval, idea generation, analysis, and response construction to AI.

However, cognitive offloading does not necessarily produce uniform outcomes. AI can reduce unnecessary cognitive demands and free resources for higher-order activities such as questioning, evaluating, comparing, and reflecting. Conversely, AI-generated information creates additional demands because students must process, filter, evaluate, and verify its outputs. When these demands accumulate, particularly under conditions of heavy reliance on AI, students could experience cognitive fatigue. Thus, cognitive load theory provides a basis for explaining both the potential negative and positive consequences of AI dependency.

AI Dependency and Critical Thinking

AI dependency reflects a more problematic reliance in which AI becomes difficult to disengage from and is associated with compulsive use or negative consequences (Goh et al., 2025). Frequent AI use does not necessarily indicate dependency, as students may use AI extensively while retaining independent judgment. In this study, AI dependency is treated as the focal antecedent.

AI dependency can challenge students' critical disposition because excessive reliance on AI can shift cognitive responsibility from the student to the technological system. When students routinely depend on AI to retrieve information, generate ideas, analyze problems, or construct arguments, they will have fewer opportunities to independently formulate questions, evaluate evidence, consider alternatives, and develop their own reasoning. Existing studies suggest that excessive reliance on AI may encourage passive learning behaviors and reduce independent cognitive processing (Karamuk, 2025; Tian & Zhang, 2025). In such circumstances, AI functions less as a cognitive resource and more as a substitute for students' own intellectual effort, potentially weakening their willingness to engage in critical examination (Hinss et al., 2022; Shetgaonkar et al., 2025).

However, AI dependency should not be assumed to inevitably produce negative consequences. AI can also support critical thinking when students interact with it actively, reflectively, and strategically (Suriano et al., 2025). AI information exposes students to multiple perspectives and alternative explanations that can stimulate comparison, evaluation, and reflection (Katsenou et al., 2025; Shaikh & Jagirdar, 2026; Suriano et al., 2025). Therefore, the relationship between AI dependency and critical thinking disposition depends on the cognitive and behavioral processes that occur during AI-supported learning.

This perspective is consistent with cognitive load theory. AI dependency can involve cognitive offloading that reduces some immediate task demands, but the consequences of this offloading depend on whether students subsequently disengage from independent thinking or redirect available cognitive resources toward higher-order learning. Accordingly, a direct relationship alone is unlikely to adequately explain the link between AI dependency and critical thinking disposition. Instead, the relationship can operate through distinct mechanisms that reflect the depletion and utilization of students' cognitive resources. In the present study, cognitive fatigue represents the negative mechanism, whereas engagement represents the positive mechanism.

Mediating Role of Cognitive Fatigue

Students facing demanding academic tasks will increasingly rely on AI to analyze information, generate ideas, and construct arguments, consistent with cognitive offloading (Risko & Gilbert, 2016; Tian & Zhang, 2025). Although offloading can reduce some task demands, AI dependency simultaneously exposes students to additional information-processing requirements. AI-generated responses are usually lengthy, complex, or ambiguous, requiring students to read, filter, evaluate, compare, and verify information. Repeated processing of such outputs may consume cognitive resources and contribute to cognitive fatigue (Shetgaonkar et al., 2025; Tian & Zhang, 2025).

Cognitive fatigue reflects a reduction in available cognitive resources after sustained mental effort and information processing. Cognitive fatigue can reduce attention, mental energy, and cognitive control (Hinss et al., 2022; Kancharla et al., 2022). When cognitively fatigued, students may rely more on shortcuts, accept information without extensive evaluation, and avoid deep analysis (Ahmed & Rasul, 2023). Such tendencies may weaken critical thinking processes, including reasoning, argument evaluation, reflection, and consideration of alternative perspectives.

Previous studies have associated prolonged technology interaction with cognitive fatigue and reduced cognitive functioning (da Silva Cezar & Maçada, 2023; Tian & Zhang, 2025). Therefore, cognitive fatigue represents a proximal cognitive-resource mechanism through which AI dependency negatively affects critical thinking disposition. Therefore, this study proposes the first hypothesis.

H1: Cognitive fatigue mediates the link between AI dependency and students' critical thinking.

Mediating Role of Engagement

According to the cognitive load theory (Sweller, 1988), cognitive offloading helps students by reducing unnecessary cognitive demands and allows them to allocate limited cognitive resources to higher-order learning activities (Risko & Gilbert, 2016). AI can handle routine aspects of academic tasks while providing information and alternative perspectives that students can use for questioning, comparing, evaluating, and reflecting. However, these benefits require cognitive engagement.

In this study, engagement refers to students' active cognitive involvement when learning with AI rather than simply the frequency or duration of AI interaction. Engaged students examine AI-generated information, ask follow-up questions, compare responses, challenge questionable claims, verify information, and refine their own ideas (Katsenou et al., 2025; Oliva-Córdova et al., 2025; Shaikh & Jagirdar, 2026). Thus, engagement reflects how students participate cognitively in AI-supported learning.

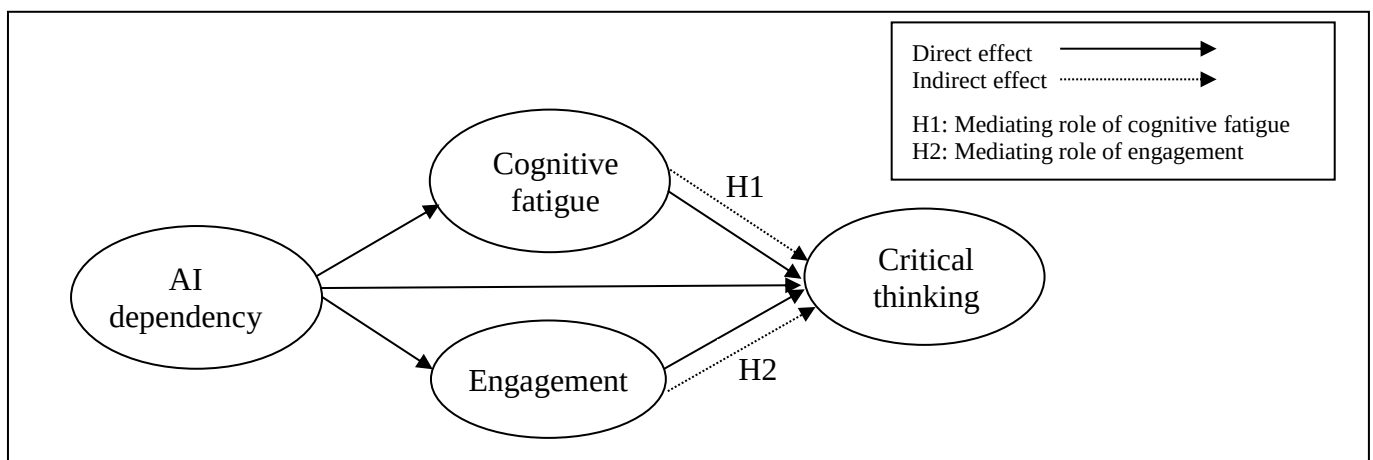
Previous study found that AI can better support critical thinking when used as a dialogue partner rather than merely an answer-providing tool. Iterative interactions involving follow-up questions, prompt refinement, challenging AI responses, and reflection can enhance critical thinking and creativity (Suriano et al., 2025). Hence, engagement allows students to use AI as a cognitive resource rather than a substitute for independent thinking. Accordingly, engagement represents the positive pathway through which AI-supported cognitive offloading may facilitate higher-order learning and critical thinking disposition. Therefore, the current study proposes the second hypothesis.

H2: Engagement mediates the link between AI dependency and students' critical thinking.

Conceptual Framework

Drawing on the literature, AI dependency among students has a dual-pathway impact on student critical thinking. When students use AI to offload cognitive demands excessively, reliance on AI may be accompanied by cognitive fatigue and reduced opportunities for independent cognitive processing, potentially weakening critical thinking disposition. Conversely, when cognitive offloading reduces unnecessary cognitive demands while students remain actively engaged with AI, the available cognitive resources could be redirected toward higher-order learning activities, potentially strengthening critical thinking disposition. Therefore, rather than assuming that AI dependency is inherently beneficial or detrimental, the present study examines whether its association with students' critical thinking disposition operates through two distinct mechanisms: cognitive fatigue as a negative pathway and engagement as a positive pathway. Accordingly, this study proposes the following conceptual model.

Figure 1
Conceptual Model



Method

Research Design

The current study employed a quantitative research design and utilized partial least squares structural equation modeling (PLS-SEM) to examine proposed hypotheses. This study examined the mediating roles of cognitive fatigue and engagement in the relationship between AI dependency and students' critical thinking.

Sampling and Sample Procedures

This study was conducted between January and March 2026 among higher education students on the island of Java, Indonesia. Java was selected as the research location because it is home to 1,477 (33.4%) of the 4,416 universities in Indonesia. This study employed a convenience sampling technique to recruit research participants because the study targeted university students who had access to AI technologies and could voluntarily participate in an online survey across geographically dispersed institutions. Participants were recruited through an online survey distributed through institutional and personal communication channels. The survey link was disseminated through email, WhatsApp, and social media platforms, including Instagram and TikTok. The recruitment message briefly described the study, eligibility requirements, voluntary nature of participation, confidentiality of responses, and the intended use of the data for research purposes. Interested students accessed the questionnaire through the survey link and proceeded to the informed-consent section before completing the questionnaire. The inclusion criteria were: (1) being currently enrolled as a higher education student in Indonesia; (2) studying at a higher education institution located in Java; and (3) having experience using AI tools for academic or learning-related activities. Responses that did not meet these criteria, contained substantial missing responses, or demonstrated an apparent lack of response quality were excluded from the analysis.

Google forms were utilized to collect data. The survey link was distributed through email, WhatsApp, and several social media platforms, including Instagram and TikTok. Participation was voluntary, and participants were informed that their data would remain confidential and anonymous. They were also informed that the collected data would be used solely for research purposes. During the survey period, a total of 683 responses were collected. The data were then screened for completeness and response quality, resulting in the exclusion of 44 responses due to suspected straight-lining. Thus, 639 responses were retained as valid, complete cases for subsequent analysis.

The adequacy of the final sample size was assessed in accordance with the characteristics of the PLS-SEM approach. Hair et al. (2019) note that PLS-SEM can provide stable parameter estimates with relatively smaller samples than covariance-based structural equation modeling (CB-SEM), particularly when estimating models with multiple constructs and indicators. Whereas CB-SEM is more strongly associated with large-sample requirements for covariance-based model estimation, PLS-SEM uses partial least squares regression to estimate the relationships among constructs and can accommodate relatively smaller samples. In the present study, the final sample of 639 valid responses provides a substantial number of observations for estimating the proposed measurement and structural models and is considered adequate for the PLS-SEM analysis.

Instruments

All variables in the current study were measured using scales adopted from previous studies and originally developed in English. To ensure the instrument was understandable to respondents, this study employed a translation and back-translation process. First, the original English items were translated into Indonesian by an English lecturer from Surabaya State University who possessed the relevant qualifications to perform the translation process. Then, the Indonesian version was subsequently back-translated into English by another English lecturer, who was independent of the initial translation. The original and back-translated versions were compared item by item to identify discrepancies in meaning, wording, and conceptual equivalence, and the discrepancies were reconciled before the pilot administration. The Indonesian version was also reviewed during the pilot study for comprehensibility and contextual appropriateness among members of the target population. Prior to distribution, the research instrument was ensured to comply with the principles of the Declaration of Helsinki.

The AI dependency variable was measured using 11 items of the Generative AI Dependency Scale developed by Goh et al. (2025), which includes three dimensions (salience and compulsive use, negative consequences, and withdrawal). Then, cognitive fatigue was measured using the four-item scale developed by Yang et al. (2026). The third variable, engagement level of AI dependency, was measured using a five-item measurement adapted from Bernava et al. (2021) and Gil-Gómez et al. (2017). Lastly, critical thinking skills were measured using 11 items from the critical thinking disposition scale by Sosu (2013), which comprises two dimensions (critical openness and reflective scepticism). All constructs in this study were measured using a five-point Likert scale, with response options ranging from 1 (strongly disagree) to 5 (strongly agree).

Pilot Study

Before administering the instruments to the full set of research participants, a pilot study was conducted involving 40 students at Universitas Negeri Surabaya. The purpose of the pilot study was to refine item clarity and to obtain preliminary psychometric evidence for the measurement model. During this process, several items of the instruments underwent several improvements and refinements. To analyze items for each subscale, this study estimated the measurement model using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. Each subscale was modeled as a reflective construct. We ran the PLS algorithm using a path weighting scheme, 300 maximum iterations, and a stop criterion of 1×10^{-7} . Item analysis was based on two criteria: (1) indicator reliability, assessed through outer loadings (factor loadings); and (2) internal consistency reliability, assessed through Cronbach's alpha. Following Hair and Alamer (2022), this study used .70 as the screening threshold for both outer loadings and

Cronbach's alpha. Items that did not meet the threshold or that were unclear were examined and revised. The results showed that all retained items had outer loadings above .70 for their respective subscales. Cronbach's alpha values for the subscales were all above .70. Several items were reworded or refined during the pilot process to improve clarity.

Data Analysis

To examine the research hypotheses, structural equation modeling (SEM) with the partial least squares (PLS) approach was employed. Since this study has two higher-order constructs (AI dependency and critical thinking), the repeated-indicator approach was used, in which all indicators of the lower-order constructs were simultaneously assigned to the higher-order constructs. The present study adopted the multistage process recommended by Hair and Alamer (2022), which includes evaluation of the measurement and structural models. In the measurement model, convergent validity was assessed using indicator loadings and Average Variance Extracted (AVE) values, discriminant validity was evaluated using the HTMT criterion, and reliability was assessed using Cronbach's alpha and composite reliability (CR). Furthermore, the structural model was evaluated by examining collinearity issues through the Variance Inflation Factor (VIF) values, the significance of path coefficients, explanatory power using R^2 values, and predictive accuracy using CVPAT. Last, to test the significance of the direct and indirect effects, a nonparametric bootstrapping procedure was employed with 5000 bootstrap resamples and a two-tailed significance level of $\alpha = .05$.

Results

First-Order Measurement Model

This stage evaluated the measurement model for the first-order constructs. The results (Table 1) show that the convergent validity of all items of the constructs meets the criteria, as factor loadings, reliability indicators, and AVE values exceed the recommended thresholds of .70, .50, and .50. Further, discriminant validity was evaluated using the HTMT (Table 2), which shows that all values were below the recommended threshold of .85, indicating that all constructs are empirically distinct from one another. Meanwhile, the reliability of all constructs was established as the value of Cronbach's alpha and composite reliability in Table 1, which ranged from .70 to .95.

Table 1

First-Order Constructs (Convergent Validity and Internal Consistency Reliability)

Constructs	Items	Convergent validity			Internal consistency reliability		
		Loadings	Indicator reliability	AVE	Cronbach's Alpha	Reliability ρ_a	Reliability ρ_c
		> .70	> .50	> .50	.70-.95	.70-.95	.70-.95
Salience & compulsive use (SCU)	SCU1	.89	.80				
	SCU2	.89	.79	.79	.87	.87	.92
	SCU3	.89	.79				
Negative consequences (NC)	NC1	.87	.76				
	NC2	.88	.78	.77	.90	.90	.93
	NC3	.87	.76				
	NC4	.88	.77				
Withdrawal (Wd)	Wdrw1	.86	.74				
	Wdrw2	.87	.76	.76	.89	.89	.93
	Wdrw3	.86	.74				
	Wdrw4	.88	.78				
Cognitive fatigue (CF)	CF1	.84	.71				
	CF2	.85	.72	.73	.88	.88	.92
	CF3	.85	.72				
	CF4	.87	.76				

Table 1 (Continued)

Constructs	Items	Convergent validity			Internal consistency reliability		
		Loadings	Indicator reliability	AVE	Cronbach's Alpha	Reliability ρ_a	Reliability ρ_c
		> .70	> .50	> .50	.70-.95	.70-.95	.70-.95
Engagement (Eng)	Eng1	.85	.73	.73	.91	.91	.93
	Eng2	.85	.73				
	Eng3	.87	.73				
	Eng4	.87	.76				
	Eng5	.85	.72				
Critical openness (CO)	CO1	.84	.63	.62	.90	.90	.92
	CO2	.85	.64				
	CO3	.85	.61				
	CO4	.87	.60				
	CO5	.80	.59				
	CO6	.80	.66				
	CO7	.78	.62				
Reflective scepticism (RS)	RS1	.80	.64	.65	.82	.82	.88
	RS2	.80	.65				
	RS3	.82	.67				
	RS4	.79	.62				

Table 2*Discriminant Validity (Heterotrait-Monotrait Ratio/HTMT)*

	SCU	NC	Wd	CF	Eng	CO	RS
SCU	-						
NC	.70	-					
Wd	.78	.72	-				
CF	.59	.59	.60	-			
Eng	.75	.72	.71	.44	-		
CO	.18	.16	.16	.26	.41	-	
RS	.18	.15	.14	.30	.42	.60	-

Note. SCU = Salience & compulsive use; NC = Negative consequences; Wd = Withdrawal; CF = Cognitive fatigue; Eng = Engagement; CO = Critical openness; RS = Reflective scepticism

Second-Order Measurement Model

This stage examined the second-order measurement model for the AI dependency and critical thinking variables, as these variables are multidimensional constructs (AI dependency comprises three dimensions, while critical thinking comprises two). The results in Table 3 indicate that convergent validity and reliability at this stage were established, as all values met the threshold.

Table 3*Second-Order Constructs (Convergent Validity and Internal Consistency Reliability)*

Variables	Dimensions	Convergent validity			Internal consistency reliability		
		Loadings	Indicator reliability	AVE	Cronbach's Alpha	Reliability ρ_a	Reliability ρ_c
		> .70	> .50	> .50	.70-.95	.70-.95	.70-.95
AI dependency	Salience & compulsive use	.96	.92	.72	.92	.92	.93
	Negative consequences	.97	.94				
	Withdrawal	.97	.93				
Critical thinking	Critical openness	.98	.96	.60	.90	.90	.93
	Reflective scepticism	.95	.90				

Structural Model

Before estimating the path coefficients in the structural model, this study employed a collinearity test to ensure the research model was free of multicollinearity among the constructs. The result shows all the variance inflation factor (VIF) under the threshold of 3.3, which indicates the current research model is free from collinearity issues, leading to the estimated path coefficients being stable and reliable.

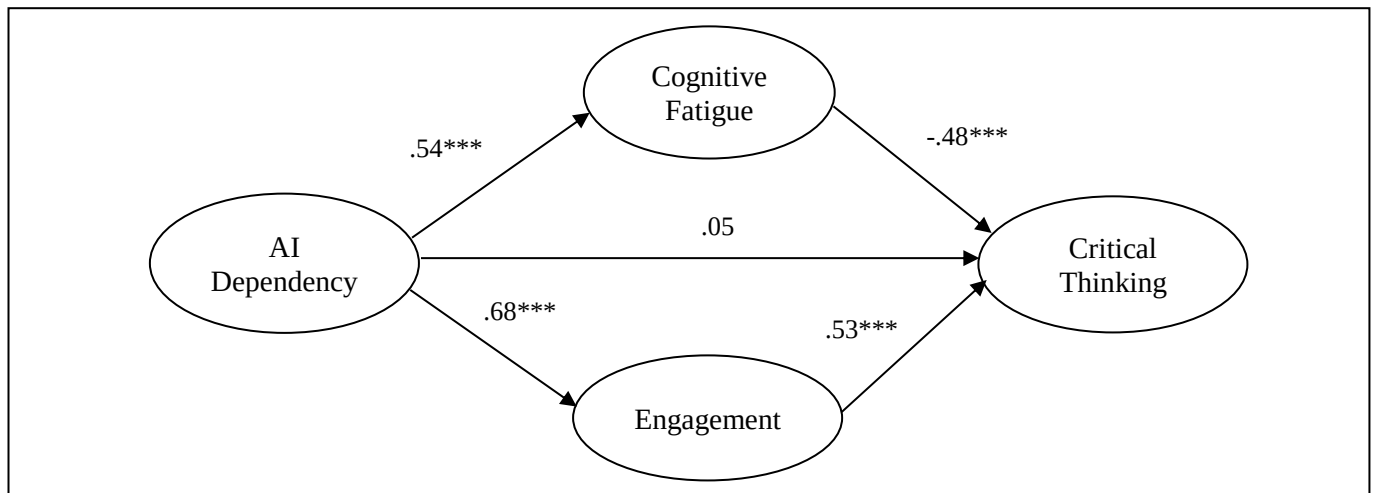
After ensuring the model is free of collinearity, this study estimates the significance of the path coefficients using a bootstrap resampling procedure with 5000 iterations. The results in Table 4 present the direct and indirect effects among AI dependency, cognitive fatigue, engagement, and critical thinking. The results indicate that AI dependency has a positive but non-significant effect on critical thinking ($\beta = .05$, $p = .31$). In contrast, AI dependency has a significant positive effect on cognitive fatigue ($\beta = .54$, $p < .001$) and engagement ($\beta = .68$, $p < .001$). Cognitive fatigue has a significant negative effect on critical thinking ($\beta = -.48$, $p < .001$), whereas engagement has a significant positive effect on critical thinking ($\beta = .53$, $p < .001$). Regarding the indirect effects, AI dependency has a significant negative effect on critical thinking through cognitive fatigue ($\beta = -.26$, $p < .001$) and a significant positive effect through engagement ($\beta = .36$, $p < .001$). These findings suggest that AI dependency is associated with critical thinking through two opposing mechanisms: cognitive fatigue is associated with lower critical thinking, whereas engagement is associated with higher critical thinking. These findings confirm both proposed hypotheses, showing that cognitive fatigue and engagement significantly mediate the link between AI dependency and critical thinking disposition. A more detailed elaboration is provided in the Discussion section.

Table 4
Path Coefficients

Path	Path coefficient	<i>p</i>	Confidence interval of path coefficient	
			2.5%	97.5%
Direct effect				
AI dependency → Critical thinking	.05	.31	-.05	.14
AI dependency → Cognitive fatigue	.54	<.001	.49	.60
AI dependency → Engagement	.68	<.001	.63	.72
Cognitive fatigue → Critical thinking	-.48	<.001	-.55	-.40
Engagement → Critical thinking	.53	<.001	.46	.61
Indirect effect				
AI dependency → Cognitive fatigue → Critical thinking	-.26	<.001	-.32	-.21
AI dependency → Engagement → Critical thinking	.36	<.001	.30	.42

This study also assessed the models' in-sample explanatory power using adjusted R^2 . The results (Figure 2) demonstrate that the current structural model has moderate explanatory power. AI dependency explains 29.4% of the variance in cognitive fatigue and 45.6% of the variance in engagement, while cognitive fatigue and engagement jointly explain 32.4% of the variance in critical thinking.

Lastly, the present study examined the models' out-of-sample predictive accuracy using CVPAT analysis by comparing the PLS loss with the LM loss. The results show that all PLS loss values for the constructs are lower than the LM loss, indicating that the PLS-SEM model in the current research produces smaller prediction errors than the benchmark linear model and thus demonstrates strong predictive accuracy. Furthermore, the *p*-values for all constructs are significant ($p < .001$), confirming the predictive accuracy of the PLS-SEM model in the current research.

Figure 2*Results of Structural Model Analysis with Standardized Path Coefficients*

Note. Path values represent standardized coefficients (β), $^{***}p < .001$, $^{**}p < .01$.

Discussion and Conclusion

The current study sought to address the contradictory findings in prior studies on the impact of AI use on students' critical thinking disposition. Drawing on cognitive load theory, this study proposes the dual pathways model to explain how AI functions as either a cognitive burden or a cognitive partner, through cognitive fatigue and engagement, and its relationship to critical thinking disposition among higher education students. The pivotal finding of the current study is that AI dependency does not directly associate with students' critical thinking disposition. This finding is crucial because it helps explain the contradiction in previous research on how AI dependency relates to critical thinking disposition. Furthermore, this finding suggests that the relationship between AI dependency and critical thinking disposition is better understood through the cognitive and behavioral processes that accompany AI-supported learning rather than through a direct association alone.

Cognitive Fatigue as a Mediating Pathway

The current study found cognitive fatigue significantly mediated the negative association between AI dependency and students' critical thinking disposition. The path coefficients show that AI dependency was positively associated with cognitive fatigue, while cognitive fatigue was negatively associated with critical thinking disposition, resulting in a significant negative indirect association. These findings are consistent with the cognitive load theory (Sweller, 1988), which proposes that working memory has limited capacity and that learning depends on how available cognitive resources are allocated during task performance. This situation has the potential to reduce students' involvement in the deep-thinking process of completing assignments. At the same time, the abundance of AI output requires students to filter and verify information. These two combinations, a lack of independent thinking activities and increased information processing demands, which drain cognitive resources, result in increased cognitive fatigue conditions (Risko & Gilbert, 2016; Tian & Zhang, 2025). When students experience cognitive fatigue, they tend to use AI passively, such as copying and pasting without critical evaluation, which ultimately reduces their critical-thinking disposition (Ahmed & Rasul, 2023; Kotnik et al., 2024; Venugopal & Vakamullu, 2025). Therefore, the use of AI induces cognitive fatigue, which acts as a cognitive burden that weakens the critical thinking disposition of students.

Furthermore, the mediation finding should not be interpreted as evidence that AI dependency necessarily causes cognitive fatigue or that cognitive fatigue necessarily causes lower critical thinking. Rather, the statistical pattern indicates that higher AI dependency was associated with greater reported cognitive fatigue, which in turn was associated with lower critical thinking disposition. The proposed

mechanism is therefore supported as an indirect association within the observed data, while the cross-sectional design does not establish temporal or causal ordering.

The current finding is consistent with the previous studies that revealed the excessive reliance on AI can be associated with passive learning behaviors and reduced independent cognitive processing (Karamuk, 2025; Tian & Zhang, 2025). The present finding also extends the literature by identifying cognitive fatigue as a proximal cognitive-resource mechanism that explains why AI dependency and critical thinking can be negatively related under some conditions. However, some mechanisms discussed in the literature require a more cautious interpretation. For example, passive AI use, such as copying and pasting AI-generated answers without critical evaluation, may plausibly accompany cognitive fatigue, but passive use was not directly measured as a mediator in the present study. Similarly, automation bias, tendency to over-rely on automated recommendations (Reicho et al., 2026; Romeo & Conti, 2026) provide a plausible explanation for why cognitive fatigue could coincide with reduced evaluation of AI outputs, but automation bias was not tested in the current model. Therefore, these mechanisms should be regarded as theoretically plausible explanations rather than established mechanisms of the present mediation.

This distinction is important because the current evidence specifically supports cognitive fatigue as the measured mediating pathway. Previous research has associated excessive technology use and prolonged human–computer interaction with cognitive fatigue and reduced cognitive functioning (Hinss et al., 2022; Kancharla et al., 2022). While the other scholar identified fatigue as a psychological mechanism relevant to the relationship between AI dependence and critical thinking (Tian & Zhang, 2025). Therefore, the current study is consistent with the previous findings while contributing a dual-pathway perspective in which the negative cognitive-resource pathway exists alongside a positive engagement pathway.

Engagement as a Mediating Pathway

The second significant finding of the current research was that engagement serves as a positive pathway between AI use and critical thinking disposition. This finding is consistent with the cognitive load theory (Sweller, 1988), particularly the proposition that cognitive offloading can reduce unnecessary cognitive demands and allow available cognitive resources to be redirected toward higher-order learning activities (Risko & Gilbert, 2016). In more detail, the use of AI can reduce unnecessary cognitive load, allowing students to focus on allocating mental resources to higher-order learning activities. Moreover, when students use AI wisely, it can serve as a cognitive partner for exploring alternative viewpoints, generating new ideas, evaluating competing arguments, and refining their understanding through iterative interactions. This process will ultimately broaden students' intellectual horizons, which are useful in developing higher-order analytical disposition.

In the present study, engagement represents a behavioral-science mechanism because it captures what students actually do with the cognitive resources made available during AI-supported learning. Engagement is not simply the frequency or duration of AI interaction. Rather, it involves active cognitive participation, including examining AI-generated information, asking follow-up questions, comparing responses, challenging questionable claims, verifying information, and refining one's own ideas (Katsenou et al., 2025; Oliva-Córdova et al., 2025; Shaikh & Jagirdar, 2026). These behaviors reflect how students allocate attention and cognitive effort while using AI and are closely related to self-regulated learning behaviors.

From a cognitive-resource perspective, AI can serve as an external cognitive resource when students use it to handle routine information-processing demands while retaining responsibility for questioning, evaluation, and reflection. In this situation, cognitive offloading does not necessarily represent cognitive disengagement. Instead, students can redistribute cognitive resources from routine task components toward higher-order activities (Risko & Gilbert, 2016). The significant positive mediation found in this study is consistent with this interpretation. However, because self-regulated learning was not directly measured, the relationship with self-regulation should be interpreted theoretically rather than as an empirically tested mechanism.

The second finding of the current research was consistent with several studies showing that the use of AI can positively impact critical thinking disposition when students engage with AI in a reflective and interactive manner rather than passively consuming AI-generated outputs (Suriano et al., 2025; Zhang & Liu, 2025). Students who are more engaged in interacting with AI, treating it as an intellectual dialogue partner, demonstrate a stronger critical thinking disposition than those who simply use AI as a tool to get instant answers (Agustinova et al., 2026; Bayly-Castaneda & Ramirez-Montoya, 2025). Similarly, iterative interactions involving prompt refinement, answer verification, challenging AI responses, and critical reflection have been associated with higher-level thinking (Kohli & Farzana, 2026; Stuchlikova & Weis, 2024). In this regard, the current study provides empirical evidence that engagement is an important mechanism explaining how AI can improve students' critical thinking disposition.

In summary, this study shows that AI dependency is not directly associated with students' critical thinking disposition, but its association operates through two opposing pathways, cognitive fatigue and engagement. Cognitive fatigue represents a negative pathway, whereby greater cognitive demands associated with AI-supported learning may be accompanied by reduced cognitive resources for critical evaluation, whereas engagement represents a positive pathway through active questioning, comparison, evaluation, and reflection. Therefore, rather than being inherently beneficial or harmful, the association between AI dependency and critical thinking disposition depends on the cognitive and behavioral processes through which students interact with AI.

Limitations

This study has several limitations that must be addressed to avoid misinterpreting its findings. First, this study employs a cross-sectional design to examine the link between variables. Accordingly, interpret the relationships found in this research model carefully and view them as associations rather than causal effects. Therefore, a longitudinal or experimental study is needed to confirm these findings. Second, the study used a sample of university students, so the results cannot be directly generalized to students at different educational levels. Future studies are recommended to expand the sample distribution across different educational levels to validate the results.

Third, this study used a self-report instrument that has the potential to introduce social desirability bias, the tendency to provide answers that are considered socially desirable (King & Bruner, 2000; Zaal et al., 2026). Future research is recommended to combine this with more objective measures, such as AI interaction logs and performance-based critical-thinking assessments. Finally, this study focused solely on cognitive fatigue and engagement as mechanisms that explain the relationship between AI dependency and critical thinking disposition. Although these two variables proved significant in bridging the relationship between the antecedent and consequence variables, the explanatory power of this model suggests that other factors could potentially influence this relationship. Future research is expected to expand the model by adding variables such as AI literacy, self-regulated learning, or automation bias to deepen our understanding of how AI dependency associated with the development of students' critical thinking disposition.

Implications for Behavioral Science

The present study provides several implications for behavioral sciences. First, interventions addressing cognitive fatigue should focus on reducing unnecessary information-processing demands rather than simply discouraging AI use. Lecturers can structure assignments into short, manageable stages to limit unnecessary AI-generated output, require students to identify the specific information they need before prompting AI, and build in brief intervals to verify or reflect on AI-generated outputs. This strategy is expected to prevent excessive cognitive demands from consuming limited cognitive resources by processing large amounts of AI-generated information. Such strategies are consistent with the view that prolonged or demanding human–technology interaction can be associated with cognitive fatigue and reduced cognitive functioning (da Silva Cezar & Maçada, 2023; Hinss et al., 2022; Kancharla et al., 2022). In AI-supported learning, reducing unnecessary processing demands helps students retain cognitive resources for evaluation and higher-order thinking.

Second, lecturers should strengthen students' reflective engagement during AI-supported learning activities. Students are encouraged to formulate initial answers independently before comparing them with AI-generated alternatives; they are asked to identify points of agreement and discrepancy, verify selected claims with scholarly sources, and explain why they accept or reject specific AI outputs. This approach aims to continuously cultivate students' critical-thinking dispositions when they use AI to address problems. These practices are consistent with research indicating that iterative interaction, questioning, verification, and reflection can support higher-order thinking when students use AI as a cognitive partner rather than merely as an answer-generating tool (Katsenou et al., 2025; Kohli & Farzana, 2026; Suriano et al., 2025). Such learning designs help maintain students' active cognitive involvement while using AI.

Third, lecturers should also develop learning strategies that build students' AI literacy and raise awareness of the risks of cognitive offloading, automation bias, and cognitive fatigue that can arise from excessive AI use. Several studies reveal that excessive reliance on external technological systems can shift cognitive responsibility away from the individual, whereas purposeful cognitive offloading can allow cognitive resources to be redirected toward higher-order activities when users remain actively involved in evaluation and decision-making (Karamuk, 2025; Risko & Gilbert, 2016; Tian & Zhang, 2025). Through this approach, students can utilize AI optimally without sacrificing the development of their critical thinking disposition.

Conclusion

This study was designed to address the relationship between AI dependency and critical thinking disposition among Indonesian higher education students through two potential pathways: cognitive fatigue and engagement. The findings indicate that AI dependency was not directly associated with critical thinking disposition but showed significant indirect associations through cognitive fatigue and engagement. Specifically, higher reported AI dependency was associated with greater cognitive fatigue, which was in turn associated with lower critical thinking disposition. Conversely, AI dependency was also positively associated with engagement, which was associated with stronger critical thinking disposition. These findings provide evidence of two contrasting pathways within the present sample and suggest that the relationship between AI dependency and critical thinking involves different cognitive and behavioral processes. However, these mediation findings should be interpreted cautiously. First, the research participants were students enrolled in higher education institutions in Indonesia. Therefore, the findings should not be generalized to students in higher education outside Indonesia or to students in other educational contexts. Second, the study used a cross-sectional design; hence, the observed associations do not establish temporal or causal relationships. In addition, self-reported measures introduce reporting bias, while convenience sampling limits the extent to which the findings can be generalized beyond the sampled university students in Indonesia. Therefore, the identified mediation patterns should be understood as evidence of statistical associations within this sample rather than as causal mechanisms that necessarily apply to students more broadly. Future longitudinal, experimental, and more diverse studies using objective measures are needed to further examine these relationships.

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Declarations

Conflicts of Interest: The authors declare no conflicts of interest.

Ethical Approval Statement: This study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Commission of Universitas Negeri Surabaya (Approval No. 00372/UN38.111.1/DL.0L010/2025; date of approval: 10 November 2025).

Declaration of Generative AI: This study uses AI tools (Grammarly and ChatGPT) for grammatical assistance only.

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