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Academic Dependency, AI Literacy, and Cognitive Offloading Predict Students' Cognitive Ability in Generative AI Learning

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ABSTRACT

Purpose – This study examines the cognitive effects of generative artificial intelligence use in higher education by testing whether academic dependency, AI literacy, and cognitive offloading predict students' cognitive ability.

Design/methods/approach – A quantitative cross-sectional survey was conducted with 93 undergraduate students at Universitas Negeri Makassar who actively use generative AI tools for academic purposes. Data were collected through a structured online questionnaire and analyzed using partial least squares structural equation modeling to evaluate measurement reliability and validity and to test structural relationships among academic dependency, AI literacy, cognitive offloading, and student cognitive ability.

Findings – The structural model shows that academic dependency, AI literacy, and cognitive offloading positively and significantly predict student cognitive ability. AI literacy is the strongest predictor, indicating that students' capacity to understand, evaluate, and use AI outputs critically is central to cognitive development. The findings also suggest that adaptive dependency can function as productive scaffolding, while strategic cognitive offloading may support higher-order thinking by reallocating limited cognitive resources.

Research implications/limitations – The cross-sectional design limits causal inference, self-reported measures may introduce bias, and a single-institution context limits generalizability.

Originality/value – This study provides integrated empirical evidence on the cognitive impact of generative AI use by jointly modeling academic dependency, AI literacy, and cognitive offloading, informing balanced AI literacy interventions and responsible AI governance in higher education.

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INTRODUCTION

The rapid development of artificial intelligence (AI) over the past five years has revolutionized various sectors, including higher education, worldwide. This technology enables a more adaptive, personalized, and efficient learning process through intelligent tutoring systems, learning analytics, and generative AI, such as ChatGPT (Crompton & Song, 2021; Hutson & others, 2022). The impact on learning is significant because AI can increase student engagement, stimulate critical thinking skills, and improve cognitive learning outcomes(Ambarita & Nurrahmatullah, 2024; Hasan et al., 2025). However, behind these benefits, there are concerns about excessive dependence on AI, which has the potential to reduce students' creativity and independent thinking skills (Cui & Alias, 2024; Pai'c & Serkin, 2025). Therefore, the academic world must maintain a balance between the use of technology and the strengthening of human cognitive capacity so that educational transformation continues to proceed in a sustainable and ethical manner.

In Indonesia, the government, through its digital education transformation policy, has begun integrating AI into the national learning system as part of its efforts to realize "Indonesia Emas 2045" (Golden Indonesia 2045). In higher education, technologies such as ChatGPT, Perplexity, and Gemini have become part of students' daily academic activities (Permata Sari et al., 2024). This use increases efficiency and aids the learning process, but at the same time, it has led to a phenomenon of dependence on artificial intelligence, which has impacted the decline in students critical and reflective thinking skills (Ding & Xue, 2025; Supriyadi et al., 2024)). The low level of digital literacy among some students also creates a gap between ideal policy and practice in the field (Supriyadi et al., 2024). Several studies have shown that although AI can increase motivation and learning effectiveness, uncontrolled use has the potential to reduce independent thinking (Badarudin et al., 2024; Dewi et al., 2025). Therefore, it is important to conduct a more in-depth study in the context of Makassar State University.

This phenomenon can be understood through John Sweller's Cognitive Load Theory (1988), which explains that the human cognitive capacity for processing information is limited. The presence of AI as a tool can ease cognitive load, but excessive use gives rise to the phenomenon of cognitive offloading, which is the tendency to surrender most of the thinking processes to digital systems. This condition leads to academic dependency, namely, students' dependence on AI in completing academic assignments, which ultimately reduces initiative and independent thinking skills (Gerlich, 2025; A. Zhang et al., 2025). Thus, this theory is an important foundation for understanding how the use of AI affects learning efficiency, independenc,e andthe quality of students thinking processes.

Previous studies have shown that AI has great potential to increase motivation, active participation, emotional engagement, and student learning outcomes through adaptive and interactive systems (Sianturi et al., 2025). Digital literacy and AI use of AI been reported to contribute significantly to improved learning outcomes (Supriyadi et al., 2024). This shows that the use of AI in higher education is complex, where benefits and potential cognitive risks can arise simultaneously, depending on the pattern of use and the level of AI literacy among students. Although AI has been proven to improve efficiency and learning outcomes, improper use has the potential to lead to undesirable cognitive consequences such as academic dependency and cognitive offloading (Gerlich, 2025; Hadinejad et al., 2025). This indicates the need for a more critical examination of how the use of AI in daily academic activities affects the quality of students' thinking processes.

However, empirical studies that specifically examine the cognitive implications of AI use in higher education still have a number of limitations. Most studies tend to focus on the benefits of AI use, such as increased motivation, efficiency, and learning outcomes, while discussions about the potential cognitive risks to students have not received equal attention. Issues such as cognitive offloading, academic dependency, and the potential decline in originality and depth of thinking are still relatively rarely explicitly examined (Ding & Xue, 2025). Kong et al. (2021) confirmed that AI literacy plays an important role in determining the quality of AI utilization in learning. Students with adequate AI literacy tended to use AI critically to support idea exploration and conceptual understanding, whereas students with low AI literacy were more prone to using AI passively and dependently. Meanwhile, Schonberg and Katz (2020) explain that the practice of cognitive offloading through digital technology can indeed increase cognitive efficiency but has the potential to reduce deep cognitive engagement in information processing.

In addition, previous studies have generally examined the variables of academic dependency, AI literacy, and cognitive offloading separately, thus failing to provide a complete picture of how these three variables interact to influence students cognitive abilities. However, recent research has shown that the use of generative AI can quickly form patterns of cognitive dependency and influence students thinking strategies in their daily academic activities (Fan et al., 2024; Gerlich, 2025).
The research gap is also evident in the limited number of empirical studies conducted in the context of higher education in developing countries, especially Indonesia. Differences in AI literacy levels, academic culture, and institutional policies have the potential to produce different patterns of AI use and impact compared to developed countries (S. Zhang et al., 2024). This condition indicates the need for contextual research that specifically examines the impact of AI use on students cognitive abilities.
This gap forms the basis of the novelty of this study. This study not only focuses on the benefits of using AI but also specifically examines how academic dependency, AI literacy, and cognitive offloading affect the cognitive abilities of students at Makassar State University, an institution that has shown a significant increase in the use of AI technology since 2024.
This study aimed to examine the effect of academic dependency, analyze the effect of AI literacy, and examine the effect of cognitive offloading on students' cognitive ability. It is hoped that the results of this study can serve as a basis for the development of more balanced AI literacy, the formulation of adaptive academic ethics policies, and encourage the productive use of AI without neglecting students independent thinking skills. Based on the previously discussed background and conceptual framework, this study formulates the following research questions
RQ1: Does Academic Dependency have a positive and significant effect on Student Cognitive Ability?
RQ2: Does AI Literacy have a positive and significant effect on Student Cognitive Ability?
RQ3: Does Cognitive Offloading have a positive and significant effect on students' cognitive ability?

METHOD

Research Design

This study adopts a quantitative approach to examine the relationship between cognitive offloading, academic dependency, and students cognitive abilities in the use of generative AI systems at Makassar State University (UNM) (Creswell & Creswell, 2018). This approach enables an empirical assessment of how academic dependency and shifts in cognitive load influence students thinking patterns in AI-based learning contexts. This study employs a cross-sectional survey design, with data collected at a single point in time to objectively examine the relationships between variables (Abduh et al., 2022). This design was selected because it can capture students actual dependence on AI without direct intervention and serves as the basis for determining sampling techniques, measurement instruments, and data analysis (Ding & Xue, 2025).

Participant

This study involved 93 respondents who were active students at the UNM. Data were collected through an online questionnaire distributed to students who met two criteria: (1) active enrollment in undergraduate courses and (2) active use of Artificial Intelligence (AI) technologies, such as ChatGPT, Gemini, or other AI-based educational platforms, to support academic activities. These criteria ensured that respondents had direct experience with generative AI systems, allowing the data to reflect students levels of dependency and cognitive abilities in the context of AI use (Badarudin et al., 2024; Supriyadi et al., 2024)

Population and the Methods of Sampling

The population of this study consisted of active students at UNM who use AI-based learning systems, including ChatGPT, Gemini, and other generative AI platforms, as UNM actively integrates digital technology into its teaching and learning processes. The sampling method employed was purposive sampling, a non-probability technique based on specific criteria that aligned with the research objectives (Fadhillah et al., 2024). Respondents were intentionally selected based on their status as active students and users of AI technology for academic purposes (Sianturi et al., 2025; Supriyadi et al., 2024). This approach is considered appropriate for higher education research that emphasizes participants specific experiences rather than broad population generalizations (Dewi et al., 2025).

Instrument

The research instrument was developed after the research design and sampling procedures were established and administered as an online questionnaire via Google Forms distributed through social media platforms such as WhatsApp. Instrument development involved the adaptation of indicators from previous studies on Cognitive Offloading, Academic Dependency, AI Literacy, and Student Cognitive Ability, followed by the formulation of statement items based on relevant theoretical frameworks. Prior to distribution, the instrument underwent content validation through expert judgment to ensure content relevance and clarity of language. All items were measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The details of the instrument items, dimensions, and sources of adaptation are presented in Table 1.

Table 1. Research Instruments

NO	Variabel	Statement	Reference
1.	*Cognitive Offloading (CO)*	1,2,3,4,5	(Gerlich, 2025)
2.	*Academic Depedencny (AD)*	6,7,8,9,10	(Acosta-Enriquez et al., 2025)
3.	*Ai Literacy (AL)*	11,12,13,14,15	(Jang, 2024)
4.	*Student Cognitive Ability (SCA)*	16,17,18,19,20	(Moneva et al., 2020)

Source: Processed data, 2025

Procedures

This study was conducted in ten systematically arranged stages, as illustrated in Figure 1.

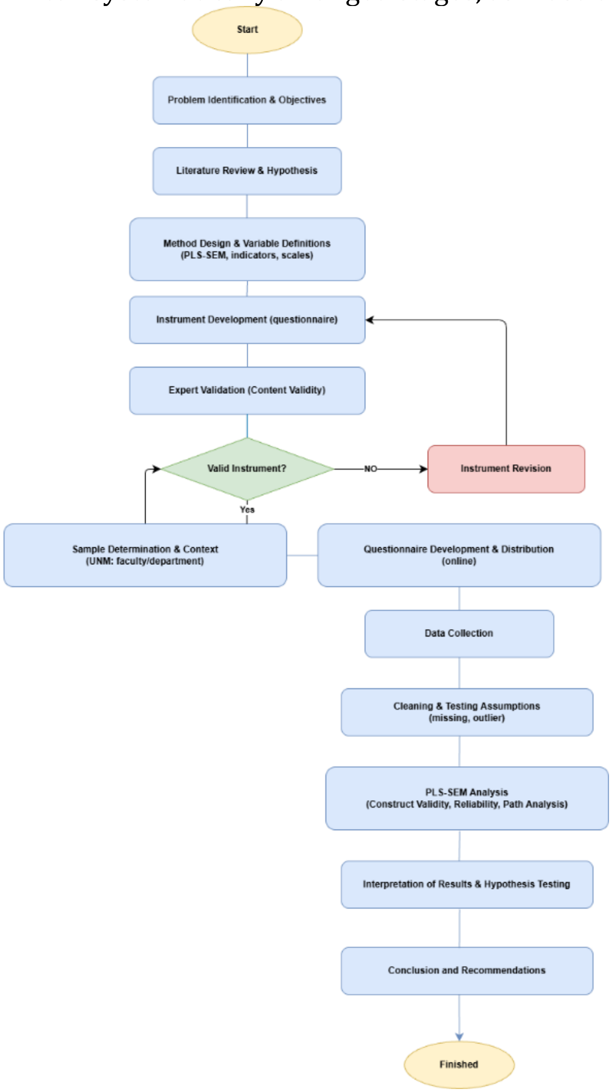

Figure 1. Research procedure flowchart

The process began with problem identification, problem formulation, and a literature review to establish the theoretical foundation and research hypotheses, followed by population and sample determination and instrument development with expert content validation. The collected data were analyzed using multivariate statistical techniques, followed by the interpretation of the findings. The final stage involved drawing conclusions and providing recommendations for further development and research.

Data Analysis

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), a multivariate statistical technique for estimating complex relationships between latent variables and their indicators. This method was selected because it is suitable for exploratory research, accommodates relatively small sample sizes, and does not require normally distributed data (J. Hair & Alamer, 2022; J. F. Hair et al., 2024). Data analysis was conducted using SmartPLS 4 in two stages: outer model analysis to assess construct validity and reliability, and inner model analysis to evaluate relationships between latent variables using path coefficients (Aurellia & Perdana, 2020; Iba & Wardhana, 2024). Jamovi was used for the preliminary descriptive analysis of the respondent characteristics. An outer model evaluation was performed to ensure that the indicators representing Academic Dependency, AI Literacy, Cognitive Offloading, and Student Cognitive Ability met validity and reliability requirements prior to structural analysis. In PLS-SEM, this evaluation focuses on the adequacy of indicators in explaining the latent variables (Cheung et al., 2024; ItHair & Alamer, 2022).d includes convergent validity, discriminant validity, and construct reliability (Li & Fah Lay, 2024).

Convergent validity was assessed using loading factors and Average Variance Extracted (AVE) values, where loading values above 0.70 indicated a substantial contribution to the construct (Cheung et al., 2024; Li & Fah Lay, 2024), and AVE values exceeding 0.50 indicated adequate explained variance (Rasoolimanesh, 2022). Consistent with common PLS-SEM practice, indicators with insufficient representation may be removed to enhance construct stability(J. F. Hair & Sabol, 2025). Discriminant validity was evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT), with HTMT values below 0.90 indicating adequate discriminant validity (Rasoolimanesh, 2022). Reliability was assessed using Composite Reliability (CR) and Cronbach's alpha, with values above 0.70 indicating satisfactory internal consistency (J. Hair & Alamer, 2022; Li & Fah Lay, 2024).

After all indicators satisfied the outer model criteria, the analysis proceeded to the inner model to test the causal relationships among constructs, specifically the effects of Academic Dependency, AI Literacy, and Cognitive Offloading on Student Cognitive Ability (J. Hair & Alamer, 2022). The significance of the path coefficients was examined using a bootstrapping procedure based on the path coefficients, *t*-statistics, and *p*-values. The results indicated that all three constructs positively influenced Student Cognitive Ability, with Academic Dependency and AI Literacy showing statistically significant effects at the 0.05 level, while Cognitive Offloading also demonstrated a positive effect with significance depending on the testing approach. Overall, the inner model evaluation clarifies the strength, direction, and significance of the relationships among variables, ensuring an accurate interpretation of the proposed structural model. The relationship between the variables is described in the following structural model, which is visualized in Figure 2.

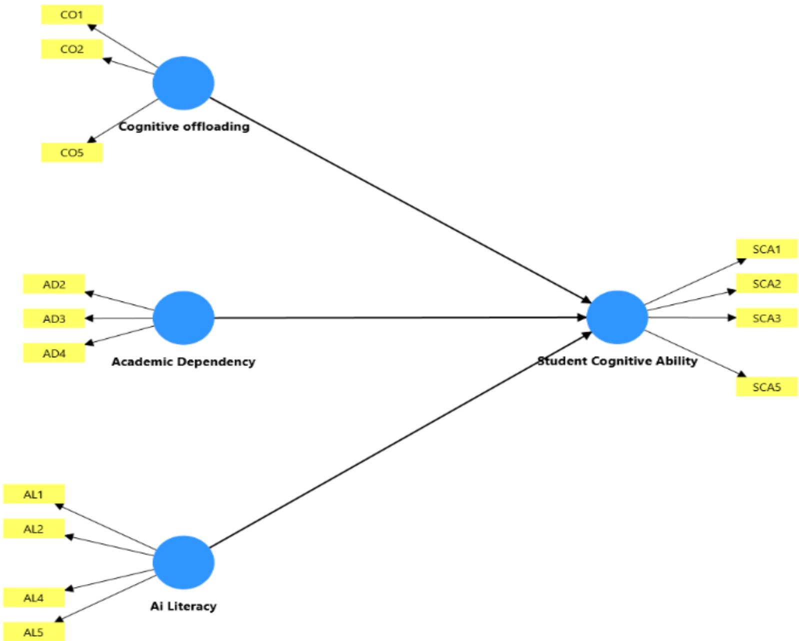

Figure 2. The model proposed in this study

Hypothesis
H1: Academic Dependency has a positive and significant effect on Student Cognitive Ability.
H2: AI Literacy has a positive and significant effect on Student Cognitive Ability.
H3: Cognitive Offloading has a positive and significant effect on students' cognitive ability.

RESULTS AND DISCUSSION

Respondent Demographic Analysis

Understanding the demographic profile of respondents is essential for contextualizing the research findings and interpreting the results appropriately. To provide a more comprehensive overview of the sample characteristics, demographic information on respondents is presented in Table 2 below, which includes key characteristics such as gender, age, semester, class year, major, digital device ownership, frequency of AI use, and the main purpose of using AI technology in academic activities.

Table 2. Respondent Demographic Data

No.	Category	Description	Percentage(%)
1.	Gender	Man	41.9%
		Woman	58.1%
2.	Age	18 years	26.9%
		19 years old	41.9%
		20 years	25.8%
		21 years	4.3%
		22 years	1.1%
3.	Semester	Semester I	25.8%
		Semester III	53.8%
		Semester V	15.1%
		Semester VII	5.4%
4.	Class Year	2022	5.4%
		2023	15.1%
		2024	53.8%
		2025	25.8%
5.	Major	STEM	80.6%
		Non-STEM	19.4%
6.	Ownership of Digital Devices	Yes	100%
		No	0%

7.	Frequency of AI Use	1–2 times/week 3–5 times/week Seldom Every day	6.5% 32.3% 2.2% 59.1%
8.	Primary Purpose of AI Use	Study the material Writing assignments Looking for references Combination(study, assignments, references)	6.5% 8.6% 18.3% 66.7%

Source: Processed data, 2025

Based on Table 2, the characteristics of the respondents show a predominance of female participants (58.1%), with the majority aged 18-20 years, with 19-year-olds being the largest group. From an academic perspective, most respondents were in their third semester (53.8%) and were from the class of 2024 (53.8%), indicating that this study mainly represents students in the early to-middle stages of their studies. The scientific background shows a high proportion of STEM disciplines (80.6%), with equal ownership of digital devices (100%). The intensity of AI utilization is also relatively high, as indicated by daily usage of 59.1%. In addition, the dominant purpose of AI use was a combination of learning activities, task completion, and reference searches (66.7%). Overall, these findings describe the profile of digital native students with a high level of technology exposure and AI adoption in the context of academic learning.

Measurement Model (Outer Model)

The evaluation of the measurement model is a crucial step in PLS-SEM analysis to ensure that the constructs are measured accurately and reliably. Table 3 shows the evaluation results for several latent constructs in the PLS-SEM model, namely, Academic Dependency (AD), AI Literacy (AL), Cognitive Offloading (CO), and Student Cognitive Ability (SCA). Each construct was measured using a number of indicators that were evaluated based on outer loadings, Rho_A, Composite Reliability (CR), and Average Variance Extracted (AVE). These parameters are used to ensure that each indicator can optimally represent its construct and meet the validity and reliability criteria in the measurement model.

Table 3. Results of Convergent Validity and Construct Reliability Evaluation

Construct and Item s	Outer Loadings	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Academic Dependency (AD)				
AD2	0.921	0.897	0.931	0.817
AD3	0.881			
AD4	0.909			
AI Literacy (AL)				
AL1	0.903	0.907	0.933	0.778
AL2	0.901			
AL4	0.847			
AL5	0.876			
Cognitive Offloading (CO)				
CO1	0.894	0.858	0.901	0.753
CO2	0.832			
CO5	0.876			
Student Cognitive Ability (SCA)				
SCA1	0.873	0.908	0.935	0.782
SCA2	0.895			
SCA3	0.889			
SCA5	0.879			

Source: Processed data, 2025

The results of the measurement model evaluation showed that all constructs of Academic Dependency (AD), AI Literacy (AL), Cognitive Offloading (CO), and Student Cognitive Ability (SCA) met the validity and reliability criteria recommended in the PLS-SEM analysis. All indicators had outer loading values above 0.80, confirming their strong contribution to their respective constructs. In the Academic Dependency construct, the Rho_A value of 0.897, Composite Reliability (CR) of 0.931, and AVE of 0.817 indicate excellent internal reliability and convergent validity. The AI Literacy construct also showed consistent measurement performance, supported by a Rho_A value of 0.907, CR of 0.933, and AVE of 0.778, all of which exceeded the recommended minimum limits. Furthermore, the Cognitive Offloading construct had a Rho_A value of 0.858, a CR of 0.901, and an AVE of 0.753, which reflects the reliability and ability of the construct to adequately explain the variance of the indicators. The Student Cognitive Ability construct also showed excellent measurement quality, with a Rho_A of 0.908, CR of 0.935, and AVE of 0.782. Overall, all constructs met the thresholds recommended by J. F. Hair et al. (2024a) namely outer loading ≥ 0.70, Rho_A and Composite Reliability values ≥ 0.70, and AVE ≥ 0.50. Thus, the measurement instruments in this study can be declared valid and reliable, providing a strong basis for the structural model evaluation stage. Table 4 shows the results of the discriminant validity test using the Fornell-Larcker criterion in the PLS-SEM model. This table includes four latent constructs that were tested: Academic Dependency (AD), AI Literacy (AL), Cognitive Offloading (CO), and Student Cognitive Ability (SCA). The analysis results showed that the AVE square root value for each construct was higher than its correlation value with other constructs. This condition indicates that each construct has adequate discriminatory ability and that there is no overlap between the variables. The detailed results of the discriminant validity test based on the Fornell-Larcker criterion are presented in Table 4.

Table 4. Results of the Fornell-Lacker Validity Test

	Academic Dependency	*Ai Literacy*	*Cognitive offloading*	*Student Ability*	*Cognitive*
Academic Dependency	**0.904**				
Ai Literacy	**0.509**	**0.882**			
Cognitive offloading	**0.297**	**0.575**	**0.868**		
Student Cognitive Ability	0.515	0.789	0.598	0.884	

Source: Processed data, 2025

The results of the discriminant validity test using the Fornell-Larcker criterion showed that all constructs in the model had good discriminant validity. The four latent constructs of Academic Dependency (AD), AI Literacy (AL), Cognitive Offloading (CO), and Student Cognitive Ability (SCA) have AVE square root values greater than the inter-construct correlations. Academic Dependency (AD) has an AVE root value of 0.904, which was higher than its correlations with the other constructs (0.509, 0.297, and 0.515). This shows that AD is a conceptually distinct construct that does not overlap with other constructs. AI Literacy (AL) has an AVE root of 0.882, which is greater than its correlations with other constructs (0.509, 0.575, and 0.789, respectively). This finding confirms that AIL can be distinguished from other constructs in the model. Cognitive Offloading (CO) has an AVE root of 0.868, which is also greater than its correlations with other constructs (0.297, 0.575, and 0.598). Thus, CO is conceptually distinct from other constructs. Student Cognitive Ability (SCA) had an AVE root value of 0.884, which was higher than its correlations with AD (0.515), AL (0.789), and CO (0.598). This indicates that the SCA is an independently measurable construct.
These results confirm that each construct in the model can be distinguished from one another, thus meeting the requirements of discriminant validity in the PLS-SEM analysis. Discriminant validity is important to ensure that each construct measures different theoretical aspects and is not overly influenced by other constructs. Thus, the observed relationships between constructs can be trusted as representations of actual theoretical relationships rather than the result of measurement

redundancy. The fulfillment of discriminant validity provides confidence that the measurement quality is adequate, allowing the analysis to proceed to the next stage, the structural model evaluation. This stage focuses on examining the path coefficients to assess the strength and direction of the relationships between the latent constructs in the model. This further analysis will provide a deeper understanding of the integrity of the structural model and the dynamics between the constructs within the research framework.

Structural Model (Inner Model)

The structural model was evaluated to examine the hypothesized relationships among the latent constructs after the measurement model met the required validity and reliability criteria. Table 5 presents the results of hypothesis testing conducted through PLS-SEM analysis, providing insight into the relationships among constructs based on path coefficients, t-statistics, and p-values, as well as the final decision regarding their significance and direction (Dewa et al., 2023).

Table 5. Results of Testing the Relationship between Latent Constructs

	Hypothesis	Path Coef	T Statistics	P Values	Decision
H1	*Academic Dependency -> Student Cognitive Ability*	0.152	2,243	0.012	Positive and Significant
H2	*AI Literacy -> Student Cognitive Ability*	0.588	3,980	0.000	Positive and significant
H3	*Cognitive offloading -> Student Cognitive Ability*	0.215	1,681	0.046	Positive and significant

Source: Processed data, 2025

The results of the hypothesis testing obtained through PLS-SEM analysis show that all relationships in the model are positive and statistically significant. Based on Table 5, hypothesis testing shows that the results of hypothesis testing through PLS-SEM analysis indicate that all relationships between variables in the model are positive and significant, where it can be seen that Academic Dependency has a positive and significant effect on Student Cognitive Ability ($\beta = 0.152$; $t = 2.243$; $p = 0.012$), thus H1 is accepted. Furthermore, AI Literacy shows the greatest influence on Student Cognitive Ability ($\beta = 0.588$; $t = 3.980$; $p = 0.000$), so H2 is accepted. Finally, Cognitive Offloading also has a positive and significant effect on Student Cognitive Ability ($\beta = 0.215$; $t = 1.681$; $p = 0.046$), so H3 is accepted. Overall, the three variables contributed positively to improving students' cognitive abilities, albeit with varying degrees of influence.

The PLS-SEM analysis results show that all relationships between the variables in the model are positive and statistically significant, confirming that Student Cognitive Ability is simultaneously influenced by Academic Dependency, AI Literacy, and Cognitive Offloading, albeit with varying degrees of influence. Empirically, AI Literacy was the most dominant predictor ($\beta = 0.588$; $t = 3.980$; $p < 0.001$), followed by Cognitive Offloading ($\beta = 0.215$; $t = 1.681$; $p = 0.046$) and Academic Dependency ($\beta = 0.152$; $t = 2.243$; $p = 0.012$).

Table 6. R Square (R^2) of Endogenous Variable

Endogenous Variable	*R Square (R^2)*
Student Cognitive Ability (SCA)	0.671

Source: Processed data, 2025

Based on the inner model evaluation, the R Square (R^2) value for Student Cognitive Ability (SCA) is 0.671. This indicates that 67.1% of the variance in students' cognitive abilities can be explained by the combined influence of Academic Dependency, AI Literacy, and Cognitive Offloading. According to J. F. Hair & Sabol, (2025) an R^2 value above 0.60 in social science research can be categorized as strong, indicating that the proposed structural model has substantial explanatory power. The remaining 32.9% is likely influenced by other factors not included in this model, such as learning motivation, self-regulation, prior knowledge, and the environment.

Discussion

These findings indicate that students cognitive abilities are not only shaped by their internal capacity but are also influenced by how they manage academic dependency, utilize technology strategically, and distribute their cognitive load through various tools. Adaptive forms of Academic Dependency, such as seeking clarification of concepts, using credible academic sources, and utilizing guidance from more competent parties, function as forms of productive dependence that strengthen knowledge structures, in line with the concept of scaffolding (Lourenço & Paiva, 2024), as well as findings that academic support can improve critical thinking and metacognitive abilities(Amanah et al., 2023; Ulandari et al., 2025). Simultaneously, the practice of cognitive offloading through the use of digital notes, information management applications, search engines, and AI technology helps reduce the burden on working memory, allowing students to focus their cognitive resources on higher-level thinking activities, in line with distributed cognition theory (A. Zhang et al., 2025), and empirical findings showing that controlled offloading can improve information processing efficiency (Fajriati et al., 2024; Maghfiroh & Widhiastuti, 2025; Mardin, 2025).

Furthermore, the dominance of AI literacy in the structural model highlights that understanding how AI functions, evaluating information credibility, recognizing potential biases, and using technology reflectively are critical determinants of students cognitive development. Students with high AI literacy are not passive consumers of AI output; instead, they actively direct, critique, and refine AI-generated information, thereby strengthening their metacognitive processes and higher-order reasoning. This phenomenon can be explained through metacognitive amplification, where technology does not replace cognition but stimulates deeper reflection, verification, and evaluation(Crompton & Song, 2021; Laupichler et al., 2022). These findings imply that the effective integration of generative AI in education depends not only on access to technology but also on students capacity to use AI strategically, critically, and reflectively. Academic dependency and cognitive offloading should not be viewed as weaknesses; when applied adaptively, they function as cognitive supports that enhance learning efficiency and conceptual understanding. The results underscore the importance of fostering AI literacy as a core educational competency to ensure that technology use strengthens rather than diminishes students' cognitive engagement.

This study contributes to the growing body of literature on Artificial Intelligence in Education (AIED) by empirically demonstrating that AI literacy is one of the strongest predictors of students' cognitive abilities. This is consistent with global research emphasizing AI literacy as a key modern competency (Laupichler et al., 2022). This study reinforces the findings that AI literacy encompasses conceptual, critical, and ethical understanding that supports complex thinking skills (Ateeq et al., 2025). Moreover, systematic reviews have confirmed that AI literacy is closely associated with improvements in analytical, reflective, and evaluative abilities in technology-enhanced learning environments (Almatrafi et al., 2024). Thus, the present findings reinforce local empirical observations and strengthen the international consensus regarding the central role of AI literacy in cognitive development within AI-based learning contexts.

Despite these contributions, this study has some limitations. First, the cross-sectional design limits the ability to capture changes in cognitive ability over time. Second, the use of perception-based measurements may have introduced subjective bias. Third, focusing on a specific digital learning context constrains the generalizability of the findings to other educational settings or populations. Future research should employ longitudinal or experimental designs to more robustly examine the causal relationships among academic dependency, cognitive offloading, AI literacy, and cognitive ability. Additionally, incorporating mediating and moderating variables, such as self-regulation, learning motivation, or epistemic beliefs, may provide deeper insight into the underlying psychological mechanisms. From a practical perspective, educational institutions should strengthen AI literacy programs and create learning environments that promote the critical, reflective, and responsible use of technology. Such efforts are essential to ensure that the benefits of generative AI enhance students' cognitive development without undermining their cognitive independence

CONCLUSION

This study demonstrates that students' cognitive ability in generative AI–supported learning is shaped by how they manage dependency, literacy, and cognitive load rather than by technology exposure alone. AI literacy emerges as the most influential predictor, indicating that cognitive benefits are likely when students can evaluate credibility, recognize limitations, and use AI outputs reflectively. Academic dependency and cognitive offloading also show positive effects, suggesting that dependency can act as scaffolding and offloading can support higher-order thinking when applied strategically and ethically. These findings imply that universities should prioritize structured AI literacy programs alongside clear academic integrity guidance and instructional designs that position AI as a learning partner rather than a cognitive substitute. The results should be interpreted cautiously due to the cross-sectional design, self-reported measures, and single-institution sample. Future studies should employ longitudinal or experimental designs, include behavioral indicators (e.g., usage logs), and test moderators such as self-regulation, epistemic beliefs, and task complexity to clarify when dependency and offloading shift from supportive to harmful.

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AUTHOR CONTRIBUTION STATEMENT
AF conceptualized the study, developed the research framework, and drafted the manuscript. RR contributed to instrument development, data collection, and data cleaning. AR performed the statistical analysis using partial least squares structural equation modeling and supported interpretation of results. All authors reviewed, revised, and approved the final manuscript and agreed to be accountable for all aspects of the work.

AI DISCLOSURE STATEMENT
The authors declare that generative AI tools were used solely to support language editing, clarity, and readability during manuscript preparation. AI tools were not used to generate research ideas, design the study, collect data, conduct statistical analysis, interpret results, or draw conclusions. All AI-assisted text was reviewed and edited by the authors, who take full responsibility for the accuracy, originality, and integrity of the manuscript.

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