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AI Literacy, AI Dependency, and Computational Thinking Skills of University Students in Linear Algebra Learning: A PLS-SEM Approach

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ABSTRACT
The rapid integration of Artificial Intelligence (AI) into higher education has created new opportunities for learning while raising concerns about students' cognitive autonomy. This study investigated the effects of AI literacy on AI dependency and computational thinking skills, as well as the relationship between AI dependency and computational thinking skills in Linear Algebra learning. The population comprised undergraduate students enrolled in Linear Algebra, with 120 students selected through purposive sampling based on their involvement in the course and experience with AI-supported learning. A quantitative survey method was employed, and the data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The model consisted of AI Literacy (LA), AI Dependency (KD), and Computational Thinking Skills (CT). The initial measurement model included eight LA indicators, six KD indicators, and six CT indicators. Three indicators (LA7, KD6, and CT5) were removed because their loading factors were below 0.60. After re-estimation, all retained indicators exceeded 0.70, with AVE values of 0.842, 0.844, and 0.753 for AI literacy, AI dependency, and computational thinking skills, respectively. AI literacy positively and significantly predicted AI dependency ($\beta=0.629$, $t=11.849$, $p<0.001$) and computational thinking skills ($\beta=0.527$, $t=4.893$, $p<0.001$). AI dependency had a negative but non-significant relationship with computational thinking skills ($\beta=-0.171$, $t=1.449$, $p=0.074$). The R^2 was 0.198, while effect sizes were 2.073 for AI literacy and 0.022 for AI dependency. The findings indicated that AI literacy is more influential than AI dependency in explaining students' computational thinking.

INTRODUCTION

Artificial Intelligence (AI), particularly generative AI, has rapidly become embedded in higher education and is reshaping how students search for information, obtain explanations, complete academic tasks, and solve problems. The rapid emergence of generative AI has begun to reshape educational practices, assessment, and research directions, requiring higher education institutions to reconsider how AI is integrated into teaching and learning (Chiu, 2023). The availability of conversational AI systems enables students to obtain explanations and potential solutions within seconds, creating significant opportunities for personalised and efficient learning. At the same time, this accessibility raises an urgent educational concern: how can higher education institutions ensure that students benefit from AI without allowing AI to replace their own reasoning and problem-solving processes?

This concern is particularly important because AI literacy is increasingly recognised as a multidimensional competence that involves not only the ability to operate AI tools, but also understanding how AI works, evaluating its outputs, recognising its limitations, and considering its ethical and social implications (Hornberger et al., 2023; Stolpe & Hallström, 2024; Chiu et al., 2024). A systematic review of 47 studies further confirmed that AI literacy has become an increasingly important educational construct, although its conceptualisation and assessment remain diverse across educational contexts (Almatrafi et al., 2024).

The urgency of this issue is particularly evident in the learning environment of the present study. Preliminary observations in the Linear Algebra learning environment indicated that students frequently used generative AI when solving mathematical tasks, while several students experienced difficulties in independently explaining the procedures underlying AI-generated solutions. In classroom activities, students occasionally consulted AI without first critically examining or verifying the information produced. Consequently, some AI-generated answers were found to be illogical, mathematically inappropriate, or inconsistent with the concepts and procedures previously explained during instruction. Rather than analysing the reasoning underlying an AI response, some students tended to accept the generated answer as an immediate solution. These observations indicate that the central problem is not simply the presence or frequency of AI use, but the quality of students' interaction with AI and their ability to critically evaluate AI-generated solutions.

The preliminary observations also identified a further concern related to students' dependence on AI. Although students were not generally characterised by high overall dependence on AI, stronger dependence appeared in particular situations where students perceived AI as an efficient way of obtaining an ideal answer. An especially concerning pattern emerged during semester examinations, when the use of mobile phones was not permitted, yet some students attempted to use AI discreetly to obtain answers and maximise their examination scores. This observation should not be interpreted as evidence that all students are highly dependent on AI; rather, it suggests that AI dependency may be situational and may become more pronounced when students face performance pressure or perceive AI as a means of reducing the cognitive effort required to solve a problem. From an educational perspective, this creates concerns not only about academic integrity but also about whether students are maintaining the independent reasoning required for genuine mathematical learning.

The problem becomes particularly important in Linear Algebra because successful learning requires substantially more than obtaining a correct final answer. Students are expected to decompose problems, identify relevant mathematical representations, recognise relationships and patterns, select appropriate procedures, construct sequential solutions, and evaluate whether the resulting solution is logically and mathematically valid. These processes are closely related to computational thinking, particularly decomposition, abstraction, pattern recognition, algorithmic reasoning, and evaluation. Thus, when students directly accept an AI-generated solution without examining its mathematical reasoning, the problem extends beyond inaccurate answers; it may also affect opportunities for developing the cognitive processes underlying computational thinking.

The concern regarding uncritical AI use is supported by emerging empirical research. Zhai et al. (2024), through a systematic review of 14 studies, found that over-reliance on AI dialogue systems may be associated with reduced engagement in critical thinking, analytical reasoning, and decision-making, particularly when users accept AI-generated recommendations without adequately assessing their reliability. Their review also highlights the tendency of users to favour rapid cognitive shortcuts when AI can provide seemingly efficient solutions. This concern is highly relevant to the observations in the present learning context, where students sometimes adopted AI-generated solutions without first examining whether the reasoning was consistent with the mathematical concepts taught in class.

Nevertheless, the educational implications of AI should not be reduced to the assumption that AI use is inherently harmful. AI can function as a learning scaffold when students use it to obtain alternative explanations, explore different procedures, identify errors, and verify their own reasoning. The distinction between beneficial AI use and problematic dependence therefore lies partly in students' AI literacy. Stolpe and Hallström (2024) argued that AI literacy should encompass technological knowledge, understanding of AI systems, and socio-ethical awareness. Chiu et al. (2024) similarly distinguish AI literacy from AI competency and emphasised that knowledge about AI must be accompanied by the ability to apply that knowledge appropriately, including confidence and self-reflective thinking.

Recent empirical research also demonstrates that AI literacy is not uniformly distributed among university students. Hornberger et al. (2023), in developing and validating an AI literacy test for university students, found substantial variation in AI literacy and reported higher levels among students with technical backgrounds or prior AI experience. Their findings indicate that students enter higher education contexts with different levels of prior AI knowledge and therefore may not interact with AI in the same way. Mansoor et al. (2024), in a transnational survey of 1,800 university students from four countries, likewise found significant differences in AI literacy according to nationality, academic specialisation, and academic degree. The authors emphasised the need to examine AI literacy across different student populations and to investigate intervening variables that may explain how AI literacy influences students' perceptions and AI-use intentions (Ayanwale et al., 2024).

The relationship between AI literacy and educational outcomes has also begun to receive empirical attention. Xiao et al. (2024), using structural equation modelling with 400 undergraduate students, examined the relationship between AI literacy, academic well-being, and educational attainment in online learning and demonstrated the relevance of structural models for examining complex relationships involving AI literacy in higher education. Such findings suggest that AI literacy should not be treated merely as a technical skill but as a competence potentially associated with broader educational and cognitive outcomes.

In addition, recent research has emphasised the need to develop AI literacy through structured educational interventions rather than assuming that students naturally acquire adequate AI competence through everyday use. Korte et al. (2024), for example, investigated cross-cultural online workshops designed to enhance AI literacy and showed the relevance of structured learning experiences for developing students' understanding of AI. Similarly, Chiu et al. (2024) proposed a framework incorporating technology, impact, ethics, collaboration, and self-reflection, illustrating that effective AI education requires dimensions that extend beyond operational competence.

At the same time, the rapid adoption of generative AI has generated concerns regarding assessment and academic integrity. Moorhouse et al. (2023) examined institutional guidelines on generative AI tools and assessment across leading universities and demonstrated that higher education institutions are increasingly required to reconsider assessment design and academic practices in response to generative AI. This concern is relevant to the present study because the preliminary observation of students attempting to access AI during examinations demonstrates that AI availability can create challenges not only for learning but also for the integrity of assessment. The issue reinforces the need to redesign learning and assessment in ways that emphasise explanation, reasoning, verification, and authentic demonstration of student understanding rather than answer production alone.

The distinction between AI literacy and AI dependency is therefore crucial. A student may possess substantial knowledge about AI, understand its capabilities, and use it frequently while still maintaining independent judgment. Conversely, a student may use AI less frequently overall but become highly dependent on it in high-stakes situations such as examinations or difficult problem-solving tasks. The preliminary observations in the present study are consistent with this possibility: students were not generally highly dependent on AI in routine learning, but situational dependency became visible when students faced difficult mathematical tasks or strong performance expectations. This suggests that AI dependency should not necessarily be conceptualised solely as a stable personal characteristic; it may also emerge as a context-dependent behavioural response.

This distinction creates an important research problem. Existing studies have increasingly examined AI literacy as a measurable competence and over-reliance as a potential threat to critical cognitive abilities, but relatively limited empirical work has simultaneously examined AI literacy, AI dependency, and computational thinking skills within a single structural model, particularly in mathematics and Linear Algebra learning. The available literature provides evidence for the importance of AI literacy (Hornberger et al., 2023; Stolpe & Hallström, 2024; Almatrafi et al., 2024), evidence concerning differences in students' AI literacy (Mansoor et al., 2024), evidence concerning relationships between AI literacy and educational outcomes (Xiao et al., 2024), and evidence regarding the cognitive risks of AI over-reliance (Zhai et al., 2024). However, these strands of research have largely developed separately.

Furthermore, existing research has paid relatively limited attention to the possibility that higher AI literacy may simultaneously increase students' ability to use AI and their tendency to rely on it, while the consequences of such dependence for computational thinking may be context-dependent. This represents an important theoretical issue because better AI literacy is generally considered desirable, yet increased competence may also make AI tools easier and more attractive to use for completing cognitive tasks. The present study therefore moves beyond a simple beneficial-versus-harmful view of AI and examines the interaction between these constructs within a specific mathematical learning context.

The novelty of this study lies in several aspects. First, it integrates AI literacy and AI dependency into the same structural framework, making it possible to investigate whether greater AI competence is associated with increased dependence. Second, it examines computational thinking skills as the primary cognitive outcome, rather than focusing only on general academic achievement, technology acceptance, or attitudes toward AI. Third, it places the model in the context of Linear Algebra learning, where computational and mathematical reasoning are strongly interconnected. Finally, the study is grounded in a real instructional context characterised by a clear pedagogical tension: students can benefit from AI-generated explanations and alternative solutions, but they may also accept AI answers without sufficient analysis, particularly when confronted with difficult tasks or high performance expectations. This contextual grounding differentiates the study from broader surveys of AI use and contributes evidence from mathematics learning, an area that remains less represented in the current AI-in-higher-education literature.

The methodological contribution is also relevant because the study employs PLS-SEM to examine the relationships among latent constructs. The use of multiple criteria for assessing reliability, convergent validity, and discriminant validity is consistent with current recommendations for structural equation modelling (Cheung et al., 2024). Against this background, the present study aims to empirically examine the relationships among AI literacy, AI dependency, and computational thinking skills among undergraduate students learning Linear Algebra. Specifically, the study investigates whether AI literacy is associated with AI dependency, whether AI literacy contributes to computational thinking skills, and whether AI dependency is associated with computational thinking skills.

By examining these relationships within one structural model, the study seeks to provide a more nuanced understanding of whether AI functions primarily as a cognitive support or whether dependency on AI may interfere with the development of students' independent mathematical and computational reasoning.

The significance of this research extends beyond the measurement of students' AI use. The findings are expected to inform higher education practices concerning how AI should be incorporated into mathematics learning. Rather than treating AI solely as a technology that should be restricted, the study supports the development of students who are capable of using AI critically, selectively, and responsibly, while retaining ownership of the reasoning process. Such an approach is particularly important in Linear Algebra, where the quality of learning depends not only on obtaining a correct answer but also on understanding why a solution is correct, being able to reproduce the reasoning independently, and recognising when an AI-generated solution is mathematically inappropriate.

RESEARCH METHOD

This study employed a quantitative explanatory research design using a cross-sectional survey and Partial Least Squares Structural Equation Modelling (PLS-SEM). The method was selected because the study examined relationships among latent constructs measured by multiple indicators and focused on explaining the predictive relationships between AI Literacy (LA), AI Dependency (KD), and Computational Thinking Skills (CT). PLS-SEM is appropriate for research models involving multiple latent constructs and predictive-oriented structural relationships (Hair & Alamer, 2022).

The research was conducted at Universitas Indraprasta PGRI, Jakarta, Indonesia, from January to June 2026. The population consisted of undergraduate students in the Informatics Engineering program who had experience using artificial intelligence-based technologies in academic activities. A total of 120 students participated as research respondents, and all 120 responses were retained for the final analysis. Respondents were selected based on the following criteria: active undergraduate students in the Informatics Engineering program, having experience using AI or generative AI for academic purposes, and being willing to complete the research questionnaire. Data were collected using an online structured questionnaire distributed to eligible respondents.

The research instrument consisted of 20 initial measurement indicators representing three latent constructs. AI Literacy (LA) was measured using eight indicators, AI Dependency (KD) using six indicators, and Computational Thinking Skills (CT) using six indicators. All indicators were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). AI literacy represented students' ability to understand, evaluate, and appropriately use AI technologies; AI dependency represented the extent to which students relied on AI in completing academic tasks and solving problems; while computational thinking skills represented students' ability to decompose problems, identify patterns, perform abstraction, and formulate systematic solutions.

The research procedure comprised problem identification and literature review, conceptual model development, hypothesis formulation, instrument development, questionnaire distribution, data collection and screening, measurement model evaluation, structural model evaluation, mediation analysis, and interpretation of the findings.

The hypotheses were tested using PLS-SEM. The measurement model was evaluated using outer loadings, Cronbach's alpha, composite reliability, Average Variance Extracted (AVE), and discriminant validity. Indicators with outer loadings below 0.60 were considered for removal based on their contribution to the overall reliability and validity of the construct. Based on this evaluation, three indicators, namely LA7, KD6, and CT5, were removed because their outer loadings did not meet the predetermined criterion. Importantly, no respondents were excluded from the analysis; all 120 collected responses were retained. The structural model was subsequently evaluated using path coefficients, coefficient of determination (R^2), effect size (f^2), bootstrapping statistics, and p-values. Statistical significance was assessed at $\alpha = 0.05$. This sequential evaluation of the measurement and structural models follows established PLS-SEM reporting recommendations (Hair & Alamer, 2022; Sarstedt et al., 2020).

The proposed structural model consisted of AI literacy as the exogenous construct, AI dependency as the mediating construct, and computational thinking skills as the endogenous construct. Accordingly, four hypotheses were formulated in Table 1.

Table 1. Research Hypotheses

Hypothesis	Statement
H1	AI literacy positively and significantly affects AI dependency.
H2	AI literacy positively and significantly affects computational thinking skills.
H3	AI dependency affects computational thinking skills.
H4	AI dependency mediates the relationship between AI literacy and computational thinking skills.

Data analysis was performed using SmartPLS 4. The PLS algorithm was first applied to evaluate the measurement and structural models, followed by a bootstrapping procedure with 5,000 bootstrap subsamples to assess the significance of the direct and indirect effects. The structural model was evaluated using path coefficients, coefficient of determination (R^2), effect size (f^2), and bootstrapping-based significance tests. Statistical significance was assessed at $\alpha = 0.05$. For the mediation analysis, the specific indirect effect of LA → KD → CT was examined using the bootstrapping procedure. The mediation effect was not determined merely by multiplying the coefficients of the direct paths; rather, the significance of the specific indirect effect was assessed using its bootstrapped confidence interval and p-value. This approach is consistent with established recommendations for PLS-SEM and mediation analysis (Hair et al., 2021; Hair & Alamer, 2022).

The overall analytical procedure followed a systematic sequence of problem identification, literature review, conceptual model development, hypothesis formulation, instrument development, data collection, data screening, measurement model assessment, structural model assessment, mediation analysis, hypothesis testing, and interpretation. The use of a standardised questionnaire, a clearly defined sample of 120 respondents, explicit indicator-retention criteria, SmartPLS 4, and 5,000 bootstrap subsamples provides sufficient methodological detail to support replication of the study.

RESULTS AND DISCUSSION

The empirical analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the relationships among AI Literacy (LA), AI Dependency (KD), and Computational Thinking Skills (CT) in the context of Linear Algebra learning. The proposed model positioned AI literacy as the exogenous construct, AI dependency as the potential mediating construct, and computational thinking skills as the endogenous construct.

The initial measurement model consisted of eight indicators for AI literacy, six indicators for AI dependency, and six indicators for computational thinking skills (Table 2). The structural relationships examined were AI literacy → AI dependency, AI literacy → computational thinking skills, and AI dependency → computational thinking skills, with an additional conceptual indirect pathway through AI dependency. The original research model was designed to examine not only direct relationships but also the possibility that students' dependency on AI could explain part of the relationship between AI literacy and computational thinking.

Table 2. Research Constructs and Their Roles in the Structural Model

Construct	Code	Initial Indicators	Role
AI Literacy	LA	8	Exogenous
AI Dependency	KD	6	Potential mediator
Computational Thinking Skills	CT	6	Endogenous

Fig. 1 illustrates the latent variable model to be analysed in this study.

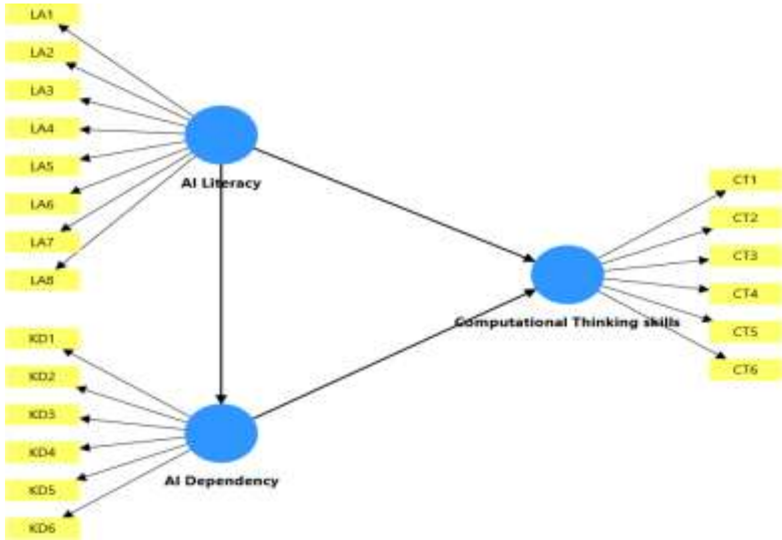

Fig 1. *Research Latent Variable Model*

The first-stage measurement assessment identified three indicators with inadequate outer loadings. CT5 had a loading of 0.433, KD6 had a loading of 0.406, and LA7 had a loading of 0.381. These indicators were removed, and the model was re-estimated (Table 3).

Table 3. Indicators were Removed

Construct	Removed Indicator	Loading
Computational thinking skills	CT5	0.433
AI dependency	KD6	0.406
AI literacy	LA7	0.381

The elimination of LA7, KD6, and CT5 indicated that these items did not adequately converge with the other indicators representing the same latent construct. Rather than interpreting the deletion as a weakness of the entire instrument, the result suggests that the three items may have captured aspects that were less consistent with the dominant dimensions represented by the retained items. This refinement resulted in a more coherent measurement model. The result is particularly relevant for AI literacy because contemporary literature conceptualises AI literacy as a multidimensional competence involving not only technical skills, but also knowledge of AI systems, practical application, critical evaluation, and social or ethical awareness.

Stolpe and Hallström (2024) emphasised that AI literacy extends beyond the ability to operate AI technologies and includes an understanding of how AI works and how humans should interact with such systems. After re-estimation, all retained indicators exceeded 0.70. CT1–CT4 and CT6 ranged from 0.826 to 0.893; KD1–KD5 ranged from 0.898 to 0.933; and LA1–LA6 and LA8 ranged from 0.905 to 0.931.

Table 4. AVE value

Construct	AVE	Interpretation
Computational thinking skills	0.753	Adequate
AI dependency	0.844	Adequate
AI literacy	0.842	Adequate

The findings are consistent with previous research showing that AI literacy can be operationalised as an empirical construct among university students. Hornberger et al. (2023) developed and validated an

AI literacy assessment for university students and demonstrated that students differ in their levels of AI literacy according to academic and experiential characteristics. The present study extends this measurement perspective by placing AI literacy within a structural model involving AI dependency and computational thinking skills in a mathematics-learning context.

All AVE values exceeded 0.50, indicating adequate convergent validity (Table 4). The results also indicated that the retained indicators explain substantial variance in their corresponding latent constructs.

Table 5. Discriminant Validity Based on the Fornell–Larcker Criterion

Construct	√AVE	Highest Inter-Construct Correlation	Conclusion
Computational thinking skills	0.868	0.419	Discriminant validity supported
AI dependency	0.919	0.629	Discriminant validity supported
AI literacy	0.917	0.629	Discriminant validity supported

The Fornell–Larcker comparison indicated that the square root of AVE for each construct is higher than its correlations with the other constructs. This supports discriminant validity (Table 5).

Table 6. Cronbach's Alpha Value

Construct	Cronbach's Alpha	Composite Reliability
Computational thinking skills	0.918	0.938
AI dependency	0.954	0.964
AI literacy	0.969	0.974

All reliability coefficients were well above conventional minimum levels, indicating strong internal consistency (Table 6). These results are important for the interpretation of the structural model because AI literacy and AI dependency, although related, should not be treated as identical concepts. A student may have a high level of AI literacy while using AI responsibly, whereas another student with similar technical competence may rely on AI more extensively. Similarly, computational thinking skills represent a distinct cognitive construct rather than simply another dimension of technology use.

Table 7. Predictive Capability of the Structural Model

Endogenous Construct	R^2	Adjusted R^2
Computational thinking skills	0.198	0.184

The R^2 value of 0.198 indicates that AI literacy and AI dependency jointly explain 19.8% of the variance in computational thinking skills (Table 7). The remaining 80.2% is attributable to factors outside the proposed model. The relatively limited R^2 does not invalidate the model. Computational thinking skills are inherently multidimensional and may be influenced by mathematical proficiency, prior programming experience, computational self-efficacy, motivation, self-regulated learning, problem-solving experience, and instructional design. The result therefore indicates that AI-related variables represent an important but incomplete component of the broader set of factors associated with computational thinking skills.

Table 8. Structural Path Results

Path	β	t-statistic	p-value	Decision
LA → KD	0.629	11.849	<0.001	Supported
LA → CT	0.527	4.893	<0.001	Supported
KD → CT	-0.171	1.449	0.074	Not supported
LA → KD → CT	-0,104	1.368	0,086	Not supported

The first structural finding indicates that AI literacy significantly and positively predicts AI dependency (Table 8). This result means that students with stronger AI literacy tend to integrate AI more intensively into their academic activities. From a technological competence perspective, this finding is reasonable because students who understand AI better are likely to know how to formulate effective prompts, identify appropriate applications, interpret AI-generated responses, and incorporate AI more efficiently into academic work. In other words, greater competence can increase the accessibility and perceived usefulness of AI.

This finding should not, however, be interpreted as evidence that AI literacy is inherently harmful. Rather, it indicates a potential paradox in AI-supported education: the same competence that enables students to use AI effectively can also make AI easier to integrate into routine academic activities. Consequently, AI literacy should be developed together with self-regulation and critical evaluation. The literature similarly emphasises that AI literacy is broader than technical operation and includes the ability to understand AI systems, assess their outputs, and engage with them appropriately (Sperling et al, 2024).

The finding is also broadly consistent with previous research on university students' AI literacy. Hornberger et al. (2023) demonstrated that students' AI literacy varies according to previous experiences and academic characteristics, suggesting that familiarity and competence with AI influence how students interact with AI systems. The cross-national study by Mansoor et al. (2024) similarly found meaningful variation in AI literacy among university students across countries, disciplines, and educational levels. These findings support the interpretation that AI literacy is an important determinant of how students engage with AI technologies rather than merely an abstract knowledge construct.

The second structural finding demonstrated a positive and significant effect of AI literacy on computational thinking skills ($\beta = 0.527$, $t = 4.893$, $p < 0.001$) (Table 8). This finding is particularly important because it suggests that AI literacy is associated not only with technological competence but also with a higher level of structured problem-solving capability. In the context of Linear Algebra, computational thinking skills involve activities such as decomposing mathematical problems, identifying patterns, determining appropriate representations, constructing sequential solution procedures, evaluating results, and generalising solutions.

One possible explanation is that students with stronger AI literacy are better able to use AI as a cognitive support mechanism rather than merely as an answer-generating system. For example, students may ask AI to produce alternative solution strategies, explain why a particular matrix operation is appropriate, identify possible errors in an initial solution, or provide conceptual clarification. When students subsequently compare and verify these outputs, AI can function as a form of scaffolding that supports higher-order cognitive processing.

This interpretation is compatible with recent conceptual frameworks distinguishing AI literacy from simple AI use. Chiu et al. (2024) argued that AI literacy and AI competency involve the ability not only to understand AI, but also to apply AI-related knowledge appropriately. The present finding extends this perspective by providing empirical evidence that AI literacy may be linked to computational thinking skills within a specific mathematics-learning context.

The result also contributes to the growing literature on AI literacy in higher education. Research by Supriyadi and Nasution (2024) on AI literacy has increasingly emphasised the need to equip students with the competence required to interact critically and effectively with AI technologies. Tzirides et al. (2024) similarly demonstrated the potential of combining human and artificial intelligence to enhance AI literacy in higher education. The present findings add an important dimension by suggesting that AI literacy may have implications for computational problem solving, particularly when AI is integrated into a domain such as Linear Algebra.

The third finding required a more cautious interpretation. AI dependency showed a negative relationship with computational thinking skills (β = -0.171), but this relationship was not statistically significant at the 5% significance level (p = 0.074) (Table 8). Therefore, the result does not provide sufficient evidence to conclude that AI dependency significantly reduces students' computational thinking skills. The negative coefficient should instead be interpreted as an observed tendency within the sample.

The negative direction is nevertheless theoretically meaningful because it is consistent with concerns about excessive reliance on AI systems. Zhai et al. (2024) systematic review found that over-reliance on AI dialogue systems can be associated with concerns about decision-making, critical thinking, and analytical reasoning, particularly when users accept AI-generated recommendations without sufficiently evaluating their reliability. Their review of 14 studies emphasised that excessive reliance may encourage cognitive shortcuts in which users favour rapid solutions over more deliberate reasoning.

The effect-size results demonstrate a substantial difference in the explanatory contribution of the two predictors (Table 9).

Table 9. Effect Size of AI literacy and AI dependency

Predictor of CT	f^2	Magnitude
AI dependency	0.022	Small
AI literacy	2.073	Large

The structural model provides a differentiated picture of the relationships among AI Literacy (LA), AI Dependency (KD), and Computational Thinking Skills (CT). AI literacy significantly predicts both AI dependency and computational thinking skills, whereas AI dependency does not have a statistically significant direct effect on computational thinking skills. The model explains 38.8% of the variance in AI dependency (R^2 = 0.388; adjusted R^2 = 0.382) and 19.8% of the variance in computational thinking skills (R^2 = 0.198; adjusted R^2 = 0.184). These results indicate that AI literacy provides meaningful explanatory power for students' AI dependency, while the combined contribution of AI literacy and AI dependency explains a more modest proportion of variation in computational thinking skills.

The first finding showed that AI literacy had a positive and statistically significant effect on AI dependency (β = 0.629, t = 11.849, p < 0.001). The R^2 value of 0.388 for AI dependency indicated that approximately 38.8% of the variance in AI dependency can be explained by AI literacy in the proposed model, while the remaining 61.2% may be associated with other factors not examined in this study. The relatively strong path coefficient, together with the explanatory power of the model, suggests that students who possess greater knowledge, familiarity, and competence in using AI are also more likely to integrate AI extensively into their academic activities.

Although this finding may initially appear counterintuitive, higher AI literacy should not necessarily be assumed to reduce AI dependency. Students who understand AI technologies better may possess greater confidence in using them, recognise a wider range of academic applications, and consequently use AI more frequently (Abbas et al., 2024). Zhang et al. (2025) similarly identified meaningful relationships among AI literacy, AI trust, AI dependency, and 21st-century skills. Zhang et al. (2024) further demonstrated that problematic AI use is associated with multiple psychological and academic factors, including academic self-efficacy, academic stress, and performance expectations. Thus, AI dependency should be understood as a multidimensional phenomenon rather than as a simple consequence of insufficient AI literacy.

The finding also emphasised the importance of distinguishing operational AI literacy from critical and self-regulatory AI literacy. Students may be highly competent in interacting with AI while lacking sufficient awareness of when AI assistance should be limited. Contemporary AI literacy frameworks emphasise not only the ability to understand and use AI but also the capacity to critically evaluate AI-generated information, recognise limitations and biases, and consider ethical implications (Almatrafi et al., 2024; Chiu et al., 2024; Walter, 2024). Consequently, AI literacy education should combine technological competence with verification skills, metacognitive awareness, and responsible use.

The second major finding indicated that AI literacy has a positive and statistically significant effect on computational thinking skills (β = 0.527, t = 4.893, p < 0.001). Moreover, the effect size of this relationship was substantial (f^2 = 2.073), indicating that AI literacy makes a strong contribution to the explanation of computational thinking skills within the proposed model (Table 9). This finding provided empirical support for positioning AI literacy as an important competency in Informatics education.

The relationship is theoretically plausible because AI literacy and computational thinking involve overlapping cognitive processes. Effective interaction with AI requires students to formulate problems clearly, decompose complex tasks, identify relevant information, evaluate generated responses, detect errors, compare alternatives, and refine solutions. These processes correspond closely to key dimensions of computational thinking, including decomposition, pattern recognition, abstraction, algorithmic reasoning, and systematic problem solving. Therefore, AI literacy may serve not merely as technological competence but also as a cognitive resource supporting computational problem solving.

This finding is consistent with Yılmaz and Karaoglan Yılmaz (2023), who reported that the use of generative AI-based tools could improve students' computational thinking skills, programming self-efficacy, and learning motivation. It is also compatible with the broader conceptualisation of AI literacy proposed by Hornberger et al. (2023) and Stolpe and Hallström (2024), in which understanding and critically evaluating AI were important components of meaningful engagement with AI technologies, while Zhong and Liu (2024) developed a framework and scale for evaluating AI literacy among secondary students. For Informatics students, these competencies are particularly relevant because students are expected not merely to consume technological outputs but to understand, evaluate, and construct computational solutions.

Nevertheless, the R^2 value of 0.198 for computational thinking skills showed that AI literacy and AI dependency jointly explain 19.8% of the variance in CT, leaving 80.2% associated with factors outside the current model. This finding is important because it prevents an overly deterministic interpretation of the significant LA → CT relationship. Computational thinking is a multidimensional competency that may also depend on programming experience, mathematical reasoning, algorithmic knowledge, problem-solving practice, academic self-efficacy, self-regulated learning, and instructional design. Thus, although AI literacy emerges as an important predictor, it should not be regarded as the sole determinant of students' computational thinking skills.

The third finding showed that AI dependency does not have a statistically significant direct effect on computational thinking skills (β = −0.171, t = 1.449, p = 0.074). Zhong and Liu (2024) developed a framework and scale for evaluating AI literacy among secondary students. Furthermore, the effect size of this relationship is small (f^2 = 0.022) (Table 9). Although the direction of the coefficient is negative, the statistical evidence is insufficient to conclude that greater AI dependency directly reduces computational thinking skills. Accordingly, H3 is not supported.

This finding offers an important nuance to concerns about students' increasing dependence on generative AI. Zhai et al. (2024) identified potential negative cognitive consequences associated with over-reliance on AI dialogue systems, while Tian and Zhang (2025) reported that AI dependence can negatively relate to critical thinking through mechanisms such as cognitive fatigue. Similarly, Essien et al. (2024) demonstrated that the use of AI text generators has important implications for students' critical thinking in higher education. Computational thinking represents a more specific set of cognitive processes involving decomposition, abstraction, pattern recognition, and algorithmic reasoning, which may be more strongly shaped by programming and problem-solving experiences than by AI dependency alone.

The small f^2 value further indicates that AI dependency contributes relatively little to explaining computational thinking skills after AI literacy is taken into account. One possible explanation is that the educational consequences of AI dependency depend on how students rely on AI rather than simply how much they rely on it. AI may function as a cognitive substitute when students accept generated solutions without verification, but it may function as a cognitive partner when students use it to obtain feedback, compare alternative solutions, identify errors, or refine their reasoning. This distinction may explain why AI dependency does not demonstrate a statistically significant direct effect on computational thinking in the present study.

The mediation analysis provides an important insight into the mechanism linking AI literacy and computational thinking skills. The specific indirect effect of AI literacy on computational thinking skills through AI dependency was negative but statistically non-significant ($\beta = -0.104$, STDEV = 0.076, $t = 1.368$, $p = 0.086$). Since the p-value exceeded the 0.05 significance threshold, H4 was not supported. Thus, AI dependency did not significantly mediate the relationship between AI literacy and computational thinking skills. This conclusion is based on the bootstrapped specific indirect effect rather than on the multiplication or separate significance of the individual path coefficients, consistent with recommended procedures for mediation analysis in PLS-SEM (Hair & Alamer, 2022; Sarstedt et al., 2020).

The non-significant mediation effect is particularly noteworthy when considered together with the direct structural relationships. AI literacy had a strong positive effect on AI dependency ($\beta = 0.629$, $t = 11.849$, $p < 0.001$) and a significant positive effect on computational thinking skills ($\beta = 0.527$, $t = 4.893$, $p < 0.001$). In contrast, AI dependency had a negative but statistically non-significant effect on computational thinking skills ($\beta = -0.171$, $t = 1.449$, $p = 0.074$). Consequently, although greater AI literacy was associated with greater AI dependency, this increased dependency did not constitute a statistically significant mechanism through which AI literacy influenced computational thinking skills.

The negative direction of the specific indirect effect ($\beta = -0.104$) nevertheless provides an interesting theoretical indication. The direct relationship between AI literacy and computational thinking skills is positive, whereas the indirect pathway through AI dependency operates in the opposite direction. This pattern suggests that the potential cognitive benefits associated with AI literacy may not be transmitted through greater dependence on AI. Rather, AI literacy appears to contribute to computational thinking skills primarily through its direct relationship, independently of the proposed mediating mechanism of AI dependency.

This result can be interpreted in relation to previous studies reporting potential cognitive risks associated with excessive reliance on AI. Zhai et al. (2024) identified concerns that over-reliance on AI dialogue systems may affect students' cognitive abilities, while Tian and Zhang (2025) found that AI dependence was negatively associated with critical thinking through psychological mechanisms such as cognitive fatigue. However, the present study extends this literature by showing that, in the context of Informatics students, AI dependency does not significantly transmit the effect of AI literacy to computational thinking skills. This suggests that AI dependency may not operate as a straightforward cognitive mechanism and that its effects may depend on other psychological, educational, or behavioural conditions.

The absence of a significant mediation effect also reinforces the distinction between AI use competence and AI reliance. AI-literate students may possess greater knowledge of AI capabilities, greater confidence in interacting with AI, and greater ability to incorporate AI into academic activities. These characteristics may explain the significant LA → KD relationship. However, increased reliance on AI does not necessarily enhance the cognitive processes involved in computational thinking skills. Computational thinking skills require students to actively engage in decomposition, abstraction, pattern recognition, algorithmic reasoning, and solution evaluation. These processes cannot necessarily be developed merely through increased interaction with or dependence on AI.

The structural model further supports this interpretation. AI literacy explained 38.8% of the variance in AI dependency ($R^2 = 0.388$; adjusted $R^2 = 0.382$), indicating that AI literacy is an important predictor of students' reliance on AI. In comparison, AI literacy and AI dependency jointly explained 19.8% of the variance in computational thinking skills ($R^2 = 0.198$; adjusted $R^2 = 0.184$). Furthermore, AI literacy demonstrated a substantial effect on computational thinking skills ($f^2 = 2.073$), whereas the effect of AI dependency was small ($f^2 = 0.022$). Taken together, these results indicate that AI literacy plays a considerably more important role than AI dependency in explaining computational thinking skills within the proposed model.

These findings therefore suggest a direct-effect-dominant model rather than a mediation-driven model. AI literacy positively contributes to computational thinking skills, but this relationship is not explained by increased AI dependency. From an educational perspective, this distinction is important. The objective of AI-integrated education should not simply be to increase students' frequency of AI use or reliance on AI systems. Instead, educational interventions should focus on developing students' capacity to understand AI, critically evaluate AI-generated information, verify outputs, recognise limitations, and integrate AI assistance with their own reasoning processes.

For Informatics education, the findings support a human-centred approach to AI literacy. This perspective is consistent with research emphasising the role of generative AI in supporting collaborative work and critical thinking when AI is integrated into learning in ways that maintain active student engagement (Ruiz-Rojas et al., 2024). Students should be encouraged to use AI as a cognitive support tool rather than a cognitive substitute. For example, AI may be used to generate alternative solutions, explain difficult concepts, detect potential programming errors, or provide feedback. However, students should remain responsible for problem decomposition, algorithm development, verification, interpretation, and justification of the final solution. Such practices may help preserve the positive relationship between AI literacy and computational thinking skills while preventing AI reliance from replacing the cognitive processes required for computational problem solving.

Overall, the combined structural results show that H1 and H2 were supported, whereas H3 and H4 were not supported. AI literacy significantly increased AI dependency and directly contributed to computational thinking skills, but AI dependency neither significantly predicted computational thinking skills nor significantly mediated the relationship between AI literacy and computational thinking skills. These findings indicate that the educational benefits associated with AI literacy are more likely to arise from students' ability to understand and critically engage with AI than from their degree of reliance on AI technology.

CONCLUSION

This study found that the measurement model for AI literacy, AI dependency, and computational thinking skills achieved acceptable validity and reliability after three indicators were removed. AI literacy positively and significantly affected AI dependency and computational thinking skills. AI dependency showed a negative but non-significant relationship with computational thinking skills. AI literacy also demonstrated a substantially larger effect size than AI dependency.

The findings suggest that AI literacy is a more important construct than AI dependency in explaining computational thinking skills within the proposed model. Higher education should therefore emphasise critical, evaluative, and responsible AI literacy. AI should be integrated as a tool for exploration, feedback, and verification rather than as a replacement for students' own reasoning. Future research should test the indirect pathway using the complete bootstrapped specific indirect-effect output and extend the model with additional cognitive and pedagogical variables.

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