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PLS-SEM Analysis of Students' AI Use: Examining the Impact of Computational Thinking and Deep Learning Skills

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ABSTRACT: The massive integration of generative artificial intelligence (AI) in higher education, particularly in scientific writing, calls for a deeper examination of the cognitive foundations underlying students' AI use. Although prior research has predominantly focused on AI adoption and attitudes, limited attention has been devoted to modeling the cognitive skills that meaningfully shape AI engagement. Addressing this gap, the present study develops and empirically tests a structural model of students' AI use by investigating the roles of Computational Thinking (CT) and Deep Learning Skills (DLS). A quantitative correlational research design was employed, involving 273 undergraduate students from three teacher education programs. Data were collected using a structured self-administered questionnaire and analyzed through Partial Least Squares–Structural Equation Modeling (PLS-SEM) to evaluate both the measurement model (reliability and validity) and the structural relationships among constructs. The results indicate that both CT and DLS significantly predict students' AI use in academic writing, with DLS demonstrating a stronger structural effect. The proposed model explains a moderate proportion of variance in AI utilization, suggesting that higher-order cognitive and learning competencies function as central determinants of effective and responsible AI engagement. These findings contribute theoretically by positioning AI use not merely as a technological adoption issue but as a cognitively grounded learning process. The study further implies that higher education curricula should systematically integrate CT and DLS development to ensure that AI serves as a cognitive augmentation tool that strengthens academic integrity and learning quality.

Keyword: AI Use; Computational Thinking; Deep Learning Skills; PLS-SEM.

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INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly transformed higher education, particularly in the ways students access information, solve problems, and support academic learning. Across universities worldwide, AI-based tools are increasingly utilized by students for tasks such as content generation, data analysis, personalized learning, and academic decision-making (Blancia et al., 2024; Li, 2024; Zafar et al., 2024). This growing integration reflects a broader shift toward digital and intelligent learning environments that emphasize efficiency and adaptability. However, the widespread availability of AI does not automatically guarantee its meaningful or productive use by students (Grassini, 2023; Purnama et al., 2023). Consequently, understanding how students engage with AI in academic contexts has become a critical issue in contemporary educational research.

In the context of higher education, particularly within teacher education programs, the use of generative AI tools such as ChatGPT has become increasingly prevalent. Pre-service teachers are not only expected to use AI to support their own academic work, including academic writing and research proposal development, but are also anticipated to develop pedagogical judgment regarding responsible and ethical AI use in future instructional settings. Despite this growing relevance, empirical evidence examining how students in teacher education programs engage with generative AI from a cognitive skill perspective remains limited. Most existing studies continue to focus on general adoption patterns or attitudes toward AI, rather than examining the cognitive competencies that shape meaningful and productive AI use in academic learning (David and Maroma, 2025; Haq et al., 2025; Saputra et al., 2025).

At UIN Kiai Ageng Muhammad Besari Ponorogo, where this study was conducted, preliminary observations and informal academic monitoring indicated that undergraduate students frequently utilize generative AI tools to assist in completing research reports and academic writing assignments. While students reported using AI to generate drafts, refine language, summarize references, and structure research proposals, classroom observations and lecturer feedback suggested that some students tended to rely on AI outputs without sufficiently engaging in critical evaluation, analytical refinement, or conceptual restructuring. This pattern reveals a discrepancy between AI-assisted productivity and cognitively grounded learning processes. Consequently, although AI is actively integrated into students' academic practices, the effective use of CT and DLS remains essential to prevent uncritical dependence and ensure meaningful knowledge construction.

Beyond the frequency of use, the effective and responsible utilization of AI requires students to possess adequate cognitive and learning competencies. Unreflective or superficial reliance on AI may lead to reduced critical engagement, academic dependency, and ethical concerns in learning processes (Abosaq, 2025; Lane et al., 2024). Therefore, current discussions increasingly emphasize the quality, purpose, and depth of AI use rather than mere adoption levels (Grassini, 2023; Zafar et al., 2024). In this context, students' internal skills and learning approaches play a decisive role in shaping how AI supports, rather than replaces, meaningful learning. As a result, identifying key competencies that enable productive AI use has become an urgent scholarly concern.

One of the most relevant competencies in this regard is CT, which has been widely recognized as a core cognitive of the twenty-first century skill. CT encompasses problem decomposition, algorithmic reasoning, abstraction, and logical decision-making (Ria et al., 2025; Ria and Susilowati, 2023b,a), all of which are essential for interacting effectively with digital technologies (Asirit and Hua, 2023; Yola et al., 2024). In educational settings, CT supports students in understanding how technological systems function and how problems can be solved systematically using computational approaches. Moreover, CT equips learners with the ability to evaluate technological outputs critically rather than accepting them unconditionally (Campbell et al., 2025). Thus, CT is increasingly viewed as a foundational skill that shapes students' capacity to engage thoughtfully with generative AI tools such as ChatGPT (Ria and Yuda, 2025).

In addition to CT, DLS represents another crucial dimension influencing students' interaction with AI. DLS refer to learners' ability to process information at a higher cognitive level, achieve conceptual understanding, engage in critical reflection, and transfer knowledge across contexts (Choi et al., 2024; Li et al., 2023). Within AI-supported learning environments, deep learning skills enable students to interpret AI-generated outputs meaningfully and integrate them into their own reasoning processes. However, existing research on DLS has primarily focused on learning outcomes and instructional strategies, with limited attention to its role in shaping technology use (Li, 2024; Yola et al., 2024). Consequently, the cognitive depth underlying students' AI engagement remains insufficiently explored.

Despite the increasing attention to AI use, CT, and DLS in education, empirical studies that model their relationships in an integrated manner remain scarce. Most prior research has examined these constructs separately or relied on descriptive and acceptance-based frameworks, offering limited explanatory insight into how higher-order skills jointly influence students' AI use (Almufarreh, 2024; Wang et al., 2024). Moreover, the limited use of predictive modeling approaches has constrained the development of comprehensive theoretical frameworks capable of explaining complex relationships among latent constructs in AI-supported learning contexts.

Given the latent, multidimensional, and conceptually complex nature of CT, DLS, and students' AI use, this study adopts PLS-SEM as the analytical approach. PLS-SEM is particularly appropriate for exploratory and predictive research aims, as it allows for the simultaneous estimation of complex structural relationships among latent variables while emphasizing predictive accuracy (Deb et al., 2023; Fan et al., 2023). This methodological approach enables a more nuanced examination of how CT and DLS collectively contribute to students' engagement with generative AI in higher education contexts.

Unlike prior studies that examine CT, DLS, and AI use as separate or loosely connected constructs, this study integrates CT and DLS within a single predictive model of students' AI use using PLS-SEM. By modeling these higher-order competencies simultaneously, the study offers a skill- oriented explanatory framework that advances understanding of how cognitive and learning skills shape meaningful engagement with generative AI technologies (Pancic et al., 2023; Vaez-Alaei et al., 2024). Accordingly, this study aims to model and predict students' use of generative AI by examining the structural relationships between CT and DLS using PLS-SEM.

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Through this approach, the study seeks to contribute to the theoretical development of AI-based learning research, provide methodological advancement through predictive modeling, and offer practical implications for instructional design and teaching and learning practice.

METHOD

This study employed a quantitative predictive correlational design to examine and model the structural relationships among CT, DLS, and students' use of generative AI in higher education. The design aligns with the study's objective of developing and testing a predictive structural model without experimental manipulation. The participants consisted of 273 undergraduate students from three academic programs Islamic Religious Education, Arabic Language Education, and Islamic Educational Management at UIN Kiai Ageng Muhammad Besari Ponorogo, Indonesia. A non-probability convenience sampling technique was applied based on participant availability and enrollment in research-related coursework. The sample size was considered adequate for PLS-SEM analysis involving multiple latent constructs and structural paths, in accordance with established methodological guidelines.

In this study, students' AI use (AIU) specifically refers to the use of generative AI tools for academic writing purposes, particularly text-based large language model platforms such as ChatGPT and similar AI systems. Students reported using these tools to generate drafts, paraphrase content, summarize references, structure research proposals, and refine academic language in research reports. Thus, AIU was operationalized as the extent to which students integrate generative AI into scientific writing and research-related academic tasks. Data were collected using a structured self-administered questionnaire measuring three latent constructs: CT, DLS, and AIU. All items were assessed using a Likert-type scale to capture students' perceptions and cognitively oriented learning behaviors. Prior to analysis, the data were screened to ensure completeness, detect potential outliers, and confirm suitability for multivariate analysis.

Data analysis was conducted using PLS-SEM, selected for its suitability in predictive modeling and complex structural relationships among latent variables. The analysis followed a two- stage approach: evaluation of the measurement model and evaluation of the structural model. The measurement model was evaluated by examining indicator reliability through outer loadings. Following Hair et al. (2021), loadings above 0.70 were considered ideal, while values between 0.40 and 0.70 were retained when supported by satisfactory construct reliability. All retained indicators demonstrated statistically significant loadings ($p < .001$). Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability ($CR \geq 0.70$), indicating strong reliability across constructs. Discriminant validity was examined through cross-loading analysis to ensure that each indicator loaded higher on its associated construct than on other constructs. Overall model fit was evaluated using the Standardized Root Mean Square Residual ($SRMR \leq 0.08$) (Subhaktiyasa, 2024). The structural model evaluation followed established PLS-SEM procedures (Boadi et al., 2022; Hair et al., 2021), including the assessment of path coefficients and their statistical significance using bootstrapping ($p < 0.05$), the coefficient of determination (R^2: 0.25 = weak, 0.50 = moderate, 0.75 = substantial), and effect size (f^2: 0.02 = small, 0.15 = medium, 0.35 = large).

RESULTS AND DISCUSSION

This section presents the results of the SEM analysis using PLS-SEM. The evaluation was conducted in two stages, including assessment of the model fit and measurement model, followed by examination of the structural relationships among the constructs. The findings are presented systematically to address the research objectives.

Model Fit Test

Tabel 1. SRMR

Index	**Value**
SRMR	0.078

Based on the analysis presented in Table 1, the SRMR value is $0.078 \leq 0.08$ (Subhaktiyasa, 2024). This result indicates that the proposed model demonstrates an acceptable level of fit. Therefore, the model can be classified as having a good overall fit.

Measurement Model Test

Tabel 2. Indicator Loadings

						95% Confidence Interval	
Construct	Indicator	**Estimate**	Std. Error	z-value	p	Lower	Upper
CT	DECO1	**0.695**	0.058	12.015	< .001	0.574	0.798
	DECO2	**0.628**	0.071	8.906	< .001	0.497	0.749
	DECO3	**0.675**	0.060	11.302	< .001	0.560	0.782
	DECO4	**0.620**	0.065	9.507	< .001	0.483	0.744

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Table 2 (continued)

						95% Confidence Interval	
Construct	Indicator	**Estimate**	Std. Error	z-value	p	Lower	Upper
	PR1	**0.468**	0.085	5.493	< .001	0.296	0.620
	PR2	**0.685**	0.063	10.862	< .001	0.538	0.787
	PR3	**0.564**	0.080	7.065	< .001	0.391	0.694
	PR4	**0.772**	0.058	13.277	< .001	0.660	0.881
	ABS1	**0.561**	0.082	6.830	< .001	0.393	0.717
	ABS2	**0.814**	0.058	14.042	< .001	0.698	0.929
	ABS3	**0.589**	0.076	7.742	< .001	0.427	0.727
	ABS4	**0.791**	0.061	12.950	< .001	0.677	0.905
	AT1	**0.829**	0.056	14.803	< .001	0.725	0.934
	AT2	**0.742**	0.059	12.551	< .001	0.623	0.844
	AT3	**0.784**	0.062	12.711	< .001	0.667	0.895
	AT4	**0.741**	0.064	11.574	< .001	0.605	0.847
	DEB1	**0.717**	0.055	13.135	< .001	0.605	0.814
	DEB2	**0.750**	0.063	11.949	< .001	0.627	0.874
	DEB3	**0.706**	0.066	10.691	< .001	0.565	0.818
	DEB4	**0.773**	0.057	13.476	< .001	0.658	0.873
DLS	CU1	**0.784**	0.052	15.188	< .001	0.681	0.884
	CU2	**0.694**	0.057	12.146	< .001	0.572	0.792
	CU3	**0.788**	0.050	15.766	< .001	0.691	0.881
	CU4	**0.698**	0.060	11.668	< .001	0.570	0.803
	CRT1	**0.662**	0.066	10.085	< .001	0.517	0.776
	CRT2	**0.819**	0.056	14.683	< .001	0.702	0.913
	CRT3	**0.792**	0.054	14.534	< .001	0.656	0.875
	CRT4	**0.782**	0.055	14.313	< .001	0.674	0.896
	IL1	**0.755**	0.055	13.645	< .001	0.634	0.848
	IL2	**0.770**	0.047	16.506	< .001	0.679	0.855
	IL3	**0.815**	0.050	16.180	< .001	0.702	0.901
	IL4	**0.795**	0.050	16.028	< .001	0.695	0.889
	MR1	**0.825**	0.045	18.513	< .001	0.741	0.908
	MR2	**0.866**	0.041	21.268	< .001	0.775	0.936
	MR3	**0.661**	0.064	10.358	< .001	0.527	0.773
	MR4	**0.672**	0.069	9.729	< .001	0.512	0.785
AIU	SP1	**0.719**	0.055	13.008	< .001	0.611	0.818
	SP2	**0.648**	0.072	8.991	< .001	0.497	0.778
	SP3	**0.475**	0.083	5.718	< .001	0.290	0.623
	SP4	**0.564**	0.065	8.682	< .001	0.442	0.680
	EK1	**0.746**	0.048	15.690	< .001	0.648	0.835
	EK2	**0.737**	0.053	13.926	< .001	0.626	0.835
	EK3	**0.767**	0.047	16.431	< .001	0.667	0.857
	EK4	**0.807**	0.049	16.611	< .001	0.706	0.887
	EA1	**0.742**	0.053	14.037	< .001	0.640	0.846
	EA2	**0.726**	0.042	17.137	< .001	0.633	0.798
	EA3	**0.619**	0.053	11.788	< .001	0.494	0.711
	EA4	**0.583**	0.070	8.348	< .001	0.436	0.691

According to the analysis presented in Table 2, all indicators demonstrate factor loading values of ≥ 0.40 (Hair et al., 2021). This finding indicates that each indicator is valid in representing the latent constructs of CT, DLS, and AIU. Therefore, the measurement model exhibits adequate convergent validity.

Tabel 3. CR

Latent	Cronbach's α
CT	0.954
DLS	0.959
AIU	0.918

Based on the analysis reported in Table 3, the Cronbach's alpha values for CT (0.954), DLS (0.959), and LD (0.918) were obtained. All these values exceed the recommended minimum threshold of 0.70 (Hair et al., 2021). Thus, the research instrument can be considered highly reliable and internally consistent in measuring the constructs under investigation.

Structural Model Test

Tabel 4. R-Squared

Outcome	R^2	Adjusted R^2
AIU	0.554	0.551

Based on the analysis presented in Table 4, the R-squared (R^2) value is 0.554, indicating that the predictor variables (CT and DLS) explain 55.4% of the variance in AIU. This value exceeds the threshold of 0.50. Therefore, the explanatory power of the model can be classified as moderate (Boadi et al., 2022; Hair et al., 2021).

Tabel 5. f^2

						95% Confidence Interval		
Outcome	**Predictor**	**Estimate**	**Std. Error**	**z-value**	**p**	**Lower**	**Upper**	**f^2**
AIU	CT	0.251	0.141	1.786	0.037	-0.027	0.550	**0.023**
	DLS	0.514	0.132	3.886	< .001	0.224	0.765	**0.105**

Based on the analysis presented in Table 5, the f^2 value for CT is 0.023, indicating a small effect size. In contrast, DLS exhibits a substantially stronger contribution to CT, with an f^2 value of 0.105. This effect size is classified as moderate (Boadi et al., 2022; Hair et al., 2021).

Regression Coefficient Test

Tabel 6. Regression Coefficient Test

Outcome	Predictor	Estimate	Std. Error	z-value	p
AIU	CT	0.251	0.141	1.786	**0.037**
	DLS	0.514	0.132	3.886	**< .001**

The regression coefficient results presented in Table 6 show that both CT and DLS significantly predict students' use of generative AI (AIU). CT has a positive effect on AIU (β = 0.251, p = 0.037), while DLS demonstrates a stronger positive effect (β = 0.514, p < 0.001) (Hair et al., 2021). These results indicate that both predictors contribute significantly to the structural model, with DLS exhibiting a higher standardized coefficient compared to CT. This finding confirms that CT and DLS function as significant predictors of AIU within the proposed PLS-SEM model. PLS-SEM was employed due to its predictive orientation and its suitability for estimating structural relationships among multiple latent constructs. The significant path coefficients support the adequacy of the proposed structural model.

The influence of CT and DLS on AI use in Academic Scientific Writing

Based on the PLS-SEM results, both CT and DLS significantly influenced students' use of AI in academic writing. CT showed a positive but small effect (β = 0.251, p = 0.037; f^2 = 0.023), whereas DLS demonstrated a stronger and highly significant contribution (β = 0.514, p < 0.001; f^2 = 0.105). CT demonstrated a positive but relatively small effect, indicating that skills such as problem decomposition, abstraction, and algorithmic reasoning support students in using AI tools in a more structured and purposeful manner during writing tasks (Kusumo et al., 2024; Li, 2025). Meanwhile, DLS showed a stronger and moderate effect, suggesting that students with higher levels of deep learning characterized by critical reflection, conceptual understanding, and meaningful information processing tend to utilize AI more intensively and responsibly in developing academic arguments and refining scholarly texts (Alhajji, 2024; Nufus et al., 2025). These findings imply that AI use in scientific writing is not merely a technical activity, but a cognitively demanding process that relies heavily on higher-order learning skills (Matueny and Nyamai, 2025; Mukunya et al., 2025). Together, CT and DLS explained a substantial proportion of variance in AI

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use, underscoring the importance of cognitive competencies in shaping productive engagement with generative AI in higher education (Kotsis, 2025; Shylla, 2025).

When linked to previous studies, these results extend prior research that largely emphasized AI adoption, attitudes, or perceived usefulness by introducing a skill-based explanatory perspective (Almufarreh, 2024; Ranabhat et al., 2024; Wang et al., 2024; Zelinski et al., 2023). Earlier works have identified CT as a foundational digital competence and DLS as a determinant of meaningful learning outcomes, yet few studies have empirically modeled their simultaneous influence on AI-supported academic writing. The novelty of this study lies in integrating CT and DLS within a single predictive framework using PLS-SEM, thereby demonstrating how these competencies jointly shape students' AI use rather than operating in isolation. This contribution advances educational research by shifting the discourse from whether students use AI to how and why they use it in academically responsible ways. For educational practice, the findings suggest that fostering CT and DLS through curriculum design and instructional strategies is crucial to ensure that AI serves as a cognitive partner in scientific writing rather than a shortcut that undermines learning integrity

CONCLUSION

This study demonstrates that both CT and DLS significantly predict students' use of generative AI in academic scientific writing. The structural model explains 55.4% of the variance in AI use (R^2 = 0.554), indicating moderate predictive power. While CT shows a positive but relatively small contribution (β = 0.251; f^2 = 0.023), DLS exerts a stronger and more substantial effect (β = 0.514; f^2 = 0.105). These findings indicate that although structured and algorithmic thinking supports AI engagement, deeper cognitive competencies play a more decisive role in fostering meaningful and strategic AI utilization in academic writing contexts.

The overall contribution of this research lies in advancing a skill-based explanatory model of AI use in higher education. By integrating CT and DLS within a predictive PLS-SEM framework, this study moves beyond prior research that primarily focused on AI adoption, perceptions, or attitudes. Instead, it provides empirical evidence that higher-order cognitive competencies jointly shape how students engage with generative AI tools in scholarly writing. The predictive orientation of PLS-SEM further strengthens the study by emphasizing variance explanation and practical contribution rather than mere statistical association.

Practically, the findings suggest that higher education institutions, particularly in teacher education programs, should prioritize the development of computational thinking and deep learning skills to ensure that generative AI functions as a cognitive partner rather than a shortcut in academic writing. Nevertheless, this study is limited by its reliance on self-reported measures, a non-probability sample from a single institutional context, and its cross-sectional design, which restrict causal inference and generalizability. Future research should adopt longitudinal or mixed-method approaches, include more diverse institutional and disciplinary contexts, and incorporate additional cognitive, ethical, and contextual variables to further clarify the determinants of responsible AI use in scholarly writing.

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DECLARATION

Contributor Roles Taxonomy

All authors contributed equally as the main contributors to this manuscript. All authors have read and approved the final version of the paper.

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