The International Journal of Business Management and Technology, Volume 10 Issue 11 November 2026
ISSN: 2581-3889

Research Article Open Access

# The Impact of Digital Literacy on Generative AI Literacy and Student Academic Performance: the Moderating Role of Self-Regulated Learning

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**Abstract:** *This study examines the structural impact of Digital Literacy (DL) on Generative AI Literacy (AL) and student Academic Performance (AP), while evaluating AL's mediating role and Self-Regulated Learning's (SRL) moderating influence. Using a quantitative research design, the study collected empirical data from 150 vocational accounting students at Politeknik Negeri Bali. It was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via WarpPLS 8.0. The statistical evaluation confirmed that Digital Literacy exerts a direct positive effect on both AI Literacy ($\beta = 0.36, p < 0.01$) and Academic Performance ($\beta = 0.32, p < 0.01$). Furthermore, AI Literacy directly enhances Academic Performance ($\beta = 0.30, p < 0.01$) and acts as a complementary partial mediator ($\beta = 0.108, p < 0.01$), showing that foundational digital skills work best when translated into specialized AI capabilities. While SRL directly drives Academic Performance ($\beta = 0.17, p = 0.02$), moderation analysis revealed that SRL significantly attenuates the AI Literacy–Academic Performance relationship ($\beta = -0.23, p < 0.01$). This dynamic indicates a compensatory scaffolding mechanism for lower-SRL students and heightened internal analytical scrutiny among high-SRL learners. The model accounts for 22.8% of the variance in Academic Performance ($R^2 = 0.228$) with strong predictive relevance ($Q^2 = 0.397$). Higher education institutions should integrate structured AI prompt-engineering curricula while actively reinforcing metacognitive self-regulation.*

**Keywords:** *academic performance, AI literacy, digital literacy, PLS-SEM, self-regulated learning*

## I. INTRODUCTION

Digital literacy serves as a foundational pillar in navigating the ongoing transformation of higher education instruction. This competency encompasses data and information literacy, communication and collaboration, cybersecurity, and the strategic use of technology to support decision-making. In Indonesia, data from the Ministry of Communication and Information Technology (2020) indicates that the national digital literacy index remains at a moderate level. Specifically, the technology capability sub-index scored 3.66, followed by communication and collaboration (3.38), cybersecurity (3.38), and data/information literacy (3.17). These metrics suggest that while technical proficiency with digital devices is relatively adequate, the capacity to process data and critically evaluate information requires further development.

Technological advancements have accelerated rapidly with the advent of Generative Artificial Intelligence (GenAI), introducing profound disruption to the higher education ecosystem [1], [2], [3]. Distinct from conventional digital technologies, GenAI simulates human cognitive processes to autonomously generate creative content, including text, images, audio, and code [4]. This paradigm shift expands student competency requirements beyond basic digital literacy toward AI literacy—defined as the capacity to understand, evaluate, engage with, and utilize AI technologies productively and ethically [4].

Ideally, digital literacy and AI literacy should directly correspond to improved learning outcomes. Students equipped with strong digital literacy tend to leverage learning resources more effectively [1], [5]. Likewise, integrating AI into educational workflows can boost learning efficiency and academic performance [6]. Nevertheless, empirical findings regarding the impact of these competencies on academic achievement remain contradictory. Several studies show that digital literacy does not significantly affect grade point averages [7] and may even have a negative effect due to technological distractions [8]. Similarly, within the AI context, reliance on GenAI tools such as ChatGPT has been associated with lower academic scores among specific student cohorts [9].

These inconsistent findings suggest a boundary condition that shapes the relationship between technology adoption and academic outcomes. In this regard, Self-Regulated Learning (SRL) may play a crucial role. Proficiency in digital tools and AI does not automatically translate into improved academic performance unless students possess self-regulatory capabilities—such as goal setting, monitoring comprehension, and managing technology usage. Without robust SRL, high AI literacy risks engendering passive reliance and cognitive offloading. Conversely, among highly self-regulated students, digital and AI tools can be deployed strategically to optimize learning outcomes.

Addressing these gaps, this study examines the impact of digital literacy on generative AI literacy and student academic performance, incorporating Self-Regulated Learning as a moderating variable. This research is novel in evaluating how SRL moderates the distinct mechanisms through which conventional digital technologies and generative AI affect academic performance. Ultimately, the findings are intended to offer an empirical foundation for higher education institutions to formulate guidelines for the productive, ethical, and responsible integration of digital and AI technologies in learning environments.

## II. Literature Review

### 2.1 Theoretical Foundations

#### 2.1.1 Constructivist Learning Theory

Constructivist Learning Theory posits that learning is an active, constructive process in which learners build internal representations of knowledge through direct experience and reflection. Within this paradigm, Vygotsky's concepts of the Zone of Proximal Development (ZPD) and scaffolding provide a foundational framework for technology-enhanced instruction [10]. Scaffolding operates through a structured continuum comprising orientation, demonstration, guidance, adaptation, and gradual fading. In modern digital learning environments, digital platforms and Generative AI (GenAI) tools serve as cognitive scaffolds that temporarily support students in solving complex academic tasks until they achieve autonomous competence.

#### 2.1.2 Technology Acceptance Model (TAM) and Self-Regulated Learning Theory

The Technology Acceptance Model (TAM) serves as a primary framework for explaining individual technology adoption [11]. TAM posits that behavioral intention to adopt technology is driven by two primary determinants: Perceived Usefulness (PU)—the degree to which an individual believes that using a system will enhance performance—and Perceived Ease of Use (PEOU)—the degree to which using a system is perceived to be free of effort. In higher education, while TAM accounts for students' willingness to adopt digital and AI tools, Self-Regulated Learning (SRL) theory complements it by explaining how students actively plan, monitor, and regulate their cognitive and behavioral processes when using these technologies.

### *2.2 Digital Literacy*

Digital literacy is a multifaceted construct encompassing the capacity to access, evaluate, manage, synthesize, and create data and information, as well as mastering digital communication, collaboration, content creation, cybersecurity, and problem-solving to support informed decision-making [12], [13], [14], [15]. [16]. Prior empirical studies suggest that higher digital literacy fosters openness to AI adoption [5] and yields positive outcomes in e-learning settings [6], [7], [17], [18]. However, empirical evidence regarding its direct impact on academic outcomes remains equivocal. While digital literacy positively correlates with communication skills, research self-efficacy, and academic confidence, its direct association with Grade Point Average (GPA) is occasionally non-significant [9]. Furthermore, digital exposure can mildly reduce academic achievement through cognitive overload or distraction, though digital literacy can act as a protective mechanism that mitigates these adverse effects [8].

### *2.3 Generative Artificial Intelligence (GenAI) Literacy*

AI literacy encompasses five core dimensions: conceptual understanding of AI principles, practical knowledge of AI applications, awareness of AI's socio-emotional impacts, adherence to safety and data privacy protocols, and responsible/ethical utilization [4]. Operationalizing AI literacy requires individuals to critically evaluate GenAI capabilities before deploying these technologies ethically. Artificial intelligence (AI) will be increasingly adopted across various domains and must therefore be held morally accountable [19], [20]. Integrating AI into accounting procedures can create ethical dilemmas that organizations must actively address [21]. Furthermore, factors contributing to AI acceptance, namely perceived usefulness, performance expectancy, attitude, trust, and effort expectancy, significantly and positively predict behavioral intention, willingness, and AI usage behavior across diverse industries [22].

Integrating AI tools in higher education has been linked to improvements in academic engagement, efficiency, and overall learning performance [1], [6], [5], [23], [24]. Moreover, foundational digital literacy directly facilitates AI

engagement in educational contexts [25]. Nevertheless, the rapid proliferation of GenAI introduces distinct pedagogical risks and ethical concerns, including algorithmic bias, disinhibition, misinformation, data privacy breaches, and diminished critical reasoning [26], [27], [28], [29]. Consequently, systematic training in GenAI literacy is required to ensure students deploy AI technologies productively without compromising academic integrity.

### *2.4 Self-Regulated Learning (SRL)*

Self-Regulated Learning (SRL) represents the degree to which students actively manage their own learning processes metacognitively, motivationally, and behaviorally [30]. SRL comprises goal setting, strategic planning, progress monitoring, and self-evaluation [30]. In technology-rich environments, SRL acts as a crucial boundary condition [31], [32]. While digital and AI tools afford rapid access to information and automated solutions, student self-regulation determines whether students use these tools for deep, strategic learning or allow them to lead to cognitive offloading and passive dependency [31], [32].

### *2.5 Academic Performance*

Academic performance reflects the extent to which a student has achieved specified educational objectives across an academic program. It is evaluated through varied assessment modalities, including written examinations, assignments, capstone projects, and class participation [33]. In quantitative educational research, researchers systematically operationalize academic performance using the Cumulative Grade Point Average (GPA). GPA provides a standardized, objective, and longitudinal measure of a student's overall academic achievement and consistency throughout their period of study.

## III. METHODS

This study employs a quantitative, explanatory research design to examine the causal relationships among digital literacy, generative AI literacy, self-regulated learning, and academic performance. The empirical investigation was conducted within the Department of Accounting at Politeknik Negeri Bali (PNB), focusing on students across three study programs: the Applied Bachelor (D4) in Managerial Accounting, the Applied Bachelor (D4) in Tax Accounting, and the Associate Degree (D3) in Accounting. The study used purposive sampling to select 150 active student respondents who met criteria aligned with the research objectives.

The research followed four systematic phases: preliminary observation and procedural design, methodological framework development, field data collection, and statistical analysis culminating in final reporting. Data were gathered from both primary and secondary sources. We collected primary data on digital literacy, generative AI literacy, self-regulated learning, and academic outcomes through structured questionnaires. All latent constructs were operationalized using a 5-point Likert scale ranging from 1 (*strongly disagree / very poor*) to 5 (*strongly agree / very good*).

Data analysis used Partial Least Squares Structural Equation Modeling (PLS-SEM), processed in WarpPLS 8.0. Descriptive statistics summarized the latent variable distributions using metrics such as minimum, maximum, median, mode, and quartile deviation. Inferential analysis followed four sequential steps: specifying the structural path model, evaluating the measurement (outer) model for validity and reliability, assessing the structural (inner) model through path coefficients, significance testing, explanatory power ($R^2$), effect sizes ($f^2$), and predictive relevance ($Q^2$).

## IV. RESULTS AND DISCUSSION

The final sample comprised 150 undergraduate accounting students, with a female-predominant distribution consisting of 84.0% female ($n = 126$) and 16.0% male respondents ($n = 24$). In terms of academic standing, the cohort spanned three study levels: second-semester students accounted for 24.0% ($n = 36$), fourth-semester students represented 35.3% ($n = 53$), and sixth-semester students constituted the largest group at 40.7% ($n = 61$). Furthermore, respondents were distributed across three specialized degree programs within the accounting department, with the highest representation from Managerial Accounting (44.7%, $n = 67$), followed by Financial Accounting (31.3%, $n = 47$) and Tax Accounting (24.0%, $n = 36$).

### *4.1 Measurement Model Evaluation*

Convergent validity was assessed by evaluating the standardized factor loadings and the Average Variance Extracted (AVE) values across all reflective constructs. As shown in the measurement model results, all indicator outer loadings exceeded the acceptable cutoff of 0.50, ranging from 0.635 to 0.811, confirming strong item-level representation. Furthermore, the AVE values for Digital Literacy (0.583), Self-Regulated Learning (0.532), and Academic Performance (0.596) surpassed the recommended 0.50 threshold, indicating that these constructs explain more than half of their items'

variance. Although the AVE for AI Literacy (0.489) fell marginally below 0.50, it remains empirically acceptable because all constituent item loadings exceeded 0.60 and its Composite Reliability reached 0.792, confirming adequate overall convergent validity across the measurement framework.

Discriminant validity was established through a tripartite assessment encompassing indicator cross-loadings, the Fornell–Larcker criterion, and the Heterotrait–Monotrait (HTMT) ratio. First, based on the measurement model evaluation, the square roots of the AVEs for Digital Literacy (0.763), AI Literacy (0.699), Self-Regulated Learning (0.729), and Academic Performance (0.772) exceeded the inter-construct correlations, satisfying the Fornell–Larcker threshold. Second, the cross-loading matrix showed that every item loaded highest on its designated parent variable rather than on competing constructs. Finally, all HTMT values remained comfortably below the conservative threshold of 0.85, providing rigorous empirical confirmation that the reflective constructs are distinct and uniquely measured within the structural framework.

Construct reliability was evaluated using Composite Reliability (CR) and Cronbach's Alpha (CA) to assess the measurement scale's internal consistency. As presented in the measurement model assessment, Composite Reliability estimates ranged from 0.792 to 0.855, comfortably surpassing the standard threshold of 0.70 and demonstrating high internal consistency across all latent constructs. Correspondingly, Cronbach's Alpha values ranged between 0.650 and 0.773. Although Cronbach's Alpha for AI Literacy (0.650) fell slightly below the conventional 0.70 benchmark, it remains methodologically acceptable in the PLS-SEM context because composite reliability provides a more nuanced and accurate measure of construct reliability, and its CR value (0.792) well exceeded the established criterion. Collectively, these statistical results confirm that all scales possess adequate internal reliability for structural model estimation.

Table 1. Measurement Model Evaluation

| Construct | Indicator | Loadings | AVE | Sq. Rts. of AVEs | CR | CA | VIF |
|---|---|---|---|---|---|---|---|
| Digital Literacy (DL) | DL1 Ability to search for digital information | 0.778 | 0.583 | 0.763 | 0.848 | 0.761 | 1.440 |
| | DL2 Ability to evaluate the credibility of information | 0.732 | | | | | |
| | DL3 Ability to utilize various digital platforms | 0.811 | | | | | |
| | DL4 Ethics in using digital technology | 0.730 | | | | | |
| AI Literacy (AL) | AL1 Understanding of generative AI concepts | 0.688 | 0.489 | 0.699 | 0.792 | 0.650 | 1.393 |
| | AL2 Ability to utilize AI tools for learning tasks | 0.635 | | | | | |
| | AL3 Ability to construct effective prompts | 0.741 | | | | | |
| | AL4 Ability to evaluate AI-generated outputs | 0.728 | | | | | |
| Self-Regulated Learning (RL) | RL1 Goal setting and study planning | 0.643 | 0.532 | 0.729 | 0.819 | 0.704 | 1.325 |
| | RL2 Monitoring of the learning process | 0.767 | | | | | |
| | RL3 Execution of self-directed learning strategies | 0.767 | | | | | |
| | RL4 Self-evaluation and reflection | 0.733 | | | | | |
| Academic Performance (AP) | AP1 Satisfactory academic grades | 0.799 | 0.596 | 0.772 | 0.855 | 0.773 | 1.594 |
| | AP2 Quality of academic assignment outputs | 0.803 | | | | | |
| | AP3 Participation in academic activities | 0.716 | | | | | |
| | AP4 Comprehension of course materials | 0.766 | | | | | |

Source: Processed data (2026)

### *4.2 Structural Model Evaluation*

#### *4.2.1 Path Coefficients and Hypothesis Testing*

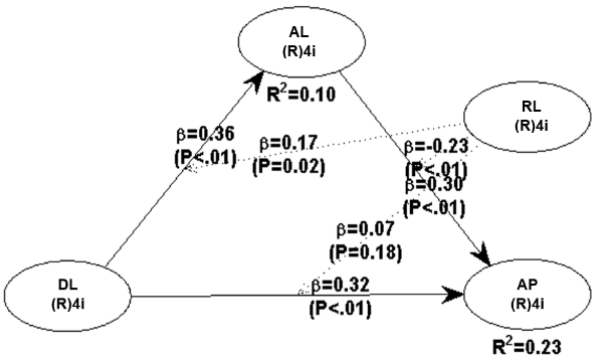



Fig. 1. Path coefficients and p-values

The evaluation of direct structural pathways demonstrates that foundational digital competencies directly drive AI capabilities and student achievement. Specifically, Digital Literacy (DL) exerts a strong and statistically significant positive effect on AI Literacy (AL) ($\beta = 0.36, p < 0.01$). Both Digital Literacy ($\beta = 0.32, p < 0.01$) and AI Literacy ($\beta = 0.30, p < 0.01$) exert direct, positive impacts on Academic Performance (AP). Furthermore, Self-Regulated Learning (RL) exhibits a significant direct positive effect on Academic Performance ($\beta = 0.17, p = 0.02$). These results confirm that digital proficiency, generative AI capabilities, and self-directed learning behaviors are meaningful individual drivers of academic success.

Regarding the indirect mechanism, AI Literacy serves as a significant mediating bridge between Digital Literacy and Academic Performance. Given the significant direct path from DL to= 0.36, p < 0.01) and from AL to AP (beta = 0.30, p < 0.01), the indirect path coefficient is calculated as beta = 0.108 (p <08 ($p < 0.01$). Because the direct relationship between Digital Literacy and Academic Performance remains statistically significant (beta = 0.32, p <0.01), AI Literacy demonstrates a complementary partial mediation effect. This finding establishes that foundational digital capabilities enhance academic performance both directly and indirectly through the development of student generative AI literacy.

In terms of interaction effects, Self-Regulated Learning (RL) yields a statistically significant negative moderating effect on the relationship between AI Literacy and Academic Performance $\beta = -0.23, p < 0.01$). This dampening effect indicates that higher self-regulation attenuates the degree to which AI literacy translates into academic performance gains. Conversely, the interaction between RL and Digital Literacy on Academic Performance is statistically non-significant ($\beta = 0.07, p = 0.18$).

#### *4.2.2 Explanatory Power*

The explanatory power of the structural model was evaluated using the coefficient of determination ($R^2$) and Stone-Geisser's adjusted $R^2$. The structural model accounted for 22.8% of the variance in Academic Performance ($R^2 = 0.228, R^2_{\text{adj}} = 0.207$) and 10.1% of the variance in AI Literacy ($R^2 = 0.101, R^2_{\text{adj}} = 0.089$), representing an acceptable level of explanatory power for educational technology studies. Regarding Cohen's effect sizes ($f^2$), AI Literacy exerted a medium effect size on Academic Performance ($f^2 = 0.150$), whereas Digital Literacy demonstrated small-to-medium effect sizes on both AI Literacy ($f^2 = 0.140$) and Academic Performance ($f^2 = 0.143$). Regarding interaction dynamics, Self-Regulated Learning exhibited a small effect size on the AI Literacy–Academic Performance pathway ($f^2 = 0.083$), while its moderating effect on the Digital Literacy–Academic Performance link was negligible ($f^2 = 0.018$).

#### *4.2.3 Predictive Relevance*

The predictive relevance of the structural model was assessed using Stone–Geisser's $Q^2$ coefficients. In PLS-SEM, a $Q^2$ statistic exceeding zero confirms that the theoretical model exhibits predictive validity for a given endogenous construct. As displayed in the evaluation results, the $Q^2$ values for AI Literacy ($Q^2 = 0.183$) and Academic Performance ($Q^2 = 0.397$) are both well above the baseline threshold of zero. Following established empirical benchmarks, the framework demonstrates medium predictive relevance for AI Literacy ($Q^2 > 0.15$) and strong predictive relevance for Academic Performance ($Q^2 > 0.35$). These findings indicate that the structural model possesses substantial capacity to predict student learning outcomes within AI-integrated educational environments.

#### *4.2.4 Multicollinearity and Model Fit*

Potential collinearity issues and common method bias (CMB) were evaluated using full collinearity Variance Inflation Factor (VIF) statistics across all latent variables. In PLS-SEM, full collinearity VIF values below the conservative threshold of 3.3 confirm that the structural model is free from vertical and lateral multicollinearity and indicate the absence of common method variance. As shown in the measurement diagnostics, the computed VIF values for Digital Literacy (VIF = 1.440), AI Literacy (VIF = 1.393), Self-Regulated Learning (VIF = 1.325), and Academic Performance (VIF = 1.594) were all well below the 3.3 benchmark. These empirical results verify that the parameter estimations are stable, methodologically robust, and uncorrupted by collinearity distortion

The empirical findings offer critical theoretical and practical insights into how digital competencies, generative AI capabilities, and metacognitive self-regulation interact to shape academic performance in modern higher education environments. The statistical results confirm that foundational digital literacy serves as an essential precursor to generative AI literacy ($\beta = 0.36, p < 0.01$), while both competencies directly drive academic performance ($\beta = 0.32, p < 0.01$ and $\beta = 0.30, p < 0.01$, respectively). Grounded in the Technology Acceptance Model (TAM) and Constructivist Learning Theory, general digital skills reduce the cognitive friction associated with adopting novel technology platforms. Students who comfortably navigate digital ecosystem interfaces, evaluate online information credibility, and practice digital ethics are far better equipped to master specialized generative AI tools—such as crafting precise prompts and critically evaluating synthetic outputs.

Furthermore, the direct positive impact of AI literacy on academic performance underscores generative AI's transformation from a mere search tool into a co-cognitive partner. In domain-specific disciplines like accounting, AI literacy enables students to accelerate data synthesis, verify complex analytical procedures, and polish written reports. These outcomes align with recent literature on AI integration in higher education (e.g., Chan & Hu, 2023; Su & Yang, 2023), which emphasizes that functional AI competence directly enhances learning productivity and coursework quality when guided by proper user knowledge.

The structural model demonstrates a statistically significant complementary partial mediation effect of AI literacy on the relationship between digital literacy and academic performance ($\beta = 0.108, p < 0.01$). This finding reveals that while general digital skills remain necessary for academic achievement, they are no longer sufficient on their own in AI-saturated academic settings. General digital proficiency achieves its maximum potential when leveraged to build specialized AI capabilities.

From a cognitive load perspective, digital literacy provides the foundational technical fluency, but AI literacy serves as the operational mechanism that converts raw digital access into tailored academic outputs. By learning how to engineer effective prompts and critically audit AI-generated content, students bridge the gap between basic technology use and higher-order academic problem-solving. This confirms that institutions cannot rely solely on traditional computer literacy modules; they must explicitly embed generative AI skill development into higher education curricula.

Self-Regulated Learning (RL) exerts a positive direct influence on academic performance ($\beta = 0.17, p = 0.02$), validating Zimmerman's classical SRL framework. Students who actively set goals, monitor their study progress, and practice self-reflection consistently achieve superior academic grades regardless of the technological environment.

However, the moderation analysis reveals a highly nuanced and intriguing dynamic: Self-Regulated Learning yields a significant negative moderating effect on the relationship between AI Literacy and Academic Performance ($\beta = -0.23, p < 0.01$). This dampening interaction can be explained through two theoretical lenses: The Compensatory Scaffolding Effect: Students with lower levels of self-regulation often struggle with task structuring, time management, and self-directed research. For these learners, high AI literacy acts as an external cognitive scaffold, compensating for their self-regulatory deficits and yielding a steeper increase in academic performance. Deep Processing and Critical Scrutiny: Conversely, highly self-regulated students rely primarily on intrinsic cognitive strategies, deep conceptual processing, and rigorous independent verification. When using generative AI, high-SRL students treat AI outputs with heightened healthy skepticism, spending considerable time cross-checking, re-evaluating, and manually refining the responses. As a result, their academic performance relies less on AI fluency itself and more on their internal analytical capabilities, dampening the marginal performance boost derived from AI literacy alone.

## V. CONCLUSION

This study provides empirical evidence on the interconnected roles of digital literacy, generative AI literacy, self-regulated learning (SRL), and academic performance among higher education students. The findings confirm that foundational digital literacy directly enhances both students' academic performance and their specialized AI literacy. Furthermore, AI literacy serves as a complementary partial mediator, showing that basic digital fluency reaches its full potential when channeled into generative AI capabilities, such as effective prompt engineering and critical evaluation of outputs. While self-regulated learning directly promotes academic achievement, it surprisingly exerts a negative moderating effect on the relationship between AI literacy and academic performance. This dynamic suggests a compensatory mechanism: AI literacy provides critical external cognitive scaffolding for students with lower self-regulation, whereas highly self-regulated students rely more on internal analytical scrutiny and independent verification. Overall, the framework underscores that generative AI literacy is a vital modern competence, but its academic benefits depend significantly on students' underlying metacognitive behaviors.

Despite its contributions, several limitations warrant acknowledgment to contextualize the findings and guide future scholarship. The sample was restricted to 150 accounting students at a single vocational polytechnic institution. Because accounting relies heavily on structured analytical tasks, the findings may not fully generalize to creative, qualitative, or clinical academic disciplines. Future research should replicate this model across multi-institutional and multi-disciplinary cohorts to test cross-field validity. The study utilized a cross-sectional approach, capturing student perceptions and self-regulatory habits at a single point in time. Given the rapid evolution of generative AI tools and evolving institutional AI policies, longitudinal or experimental research designs are recommended to track the causal trajectories of AI literacy and SRL development over time. All variables—including academic performance and AI literacy—were measured using self-reported survey items. Although statistical checks confirmed the data were free from common method bias, future studies should incorporate objective performance indicators (such as verified grade point averages, standardized prompt-engineering assessments, or LMS interaction logs) to validate subjective self-assessments.

These empirical findings offer important theoretical and practical implications for higher education in the generative AI era. Theoretically, this study extends the Technology Acceptance Model (TAM) and Self-Regulated Learning (SRL) framework by demonstrating that while AI literacy directly enhances academic performance, its marginal utility remains

deeply contingent upon a student's internal metacognitive regulation. From an institutional perspective, these insights require strategic curriculum redesign; academic institutions—particularly in technical and analytical disciplines like accounting—must shift from passive or overly restrictive AI policies to structured, practical modules that emphasize prompt engineering and critical output verification. Ultimately, educators must cultivate a balanced pedagogy that pairs AI skill development with robust self-regulated learning habits, ensuring that students maintain independent critical thinking and avoid passive cognitive offloading onto automated AI systems.

## Acknowledgements

Politeknik Negeri Bali supported this study under the DIPA Funding Scheme, Contract No. SP DIPA-139.03.2.693476/2026, dated December 1, 2025 (3rd Revision, February 18, 2026).

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