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The Impact of Generative AI Use on Academic Performance in Accounting Education: the Role of Pedagogical Capacity and Cognitive Limitations

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Abstract: *This study aims to analyze the structural relationship between Generative AI usage and the academic performance of vocational accounting students by evaluating the mediating role of pedagogical capacity and the moderating role of cognitive limitations grounded in Constructivist Learning Theory. Utilizing an explanatory quantitative approach based on Structural Equation Modeling among accounting students at Politeknik Negeri Bali, the measurement instruments were validated to meet rigorous reliability and validity standards. The results reveal a competitive mediation phenomenon, wherein direct Generative AI utilization without pedagogical guidance negatively impacts academic performance due to passive reliance and the suppression of critical thinking. Conversely, when technology usage is filtered and mediated by pedagogical capacity—namely students' ability to evaluate information accuracy and integrate AI critically—its impact becomes strongly positive in enhancing learning outcomes. Furthermore, student cognitive limitations do not significantly moderate the relationship between AI usage and academic performance. Practically, these findings demonstrate that AI technology does not inherently degrade educational quality; the key lies in the presence of guidance and evaluative pedagogical capacity. Consequently, higher education institutions should avoid banning AI, opting instead to transform its adoption through structured curricula that teach the verification of technological outputs against official accounting standards and deploy higher-order thinking assessment methods.*

Keywords: academic performance, accounting education, cognitive limitations, generative AI, pedagogical capacity

I. INTRODUCTION

The transformative trajectory of Artificial Intelligence (AI) has reconfigured contemporary higher education, fundamentally altering instructional paradigms and knowledge acquisition processes [1], [2]. Grounded in Constructivist Learning Theory, effective learning occurs when students actively construct knowledge through dynamic interactions with their educational environment. Generative AI (GenAI)—specifically large language models like ChatGPT—acts as an interactive learning scaffold, emulating complex reasoning to assist students in processing financial data and technical concepts [3].

As GenAI tools become pervasive, AI literacy has emerged as a fundamental competency for accounting undergraduates [4]. Comprising conceptual understanding, technical evaluation, and ethical stewardship, AI literacy enables students to critically engage with AI-generated outputs [3], [5], [6]. In accounting education, GenAI demonstrates substantial pedagogical capacity by serving as a personalized tutor that simplifies technical principles, scaffolds procedural problem-solving, and accelerates learning efficiency [3]. However, the educational benefit of this pedagogical tool is not automatic; it depends heavily on how students internalize and process information.

A critical, yet underresearched, bottleneck in constructivist AI learning is the role of students' cognitive limitations. While GenAI provides rich instructional scaffolding, processing complex, AI-generated accounting logic places a heavy cognitive load on students. Undergraduates often face cognitive constraints—such as limited working memory capacity, reduced critical evaluation skills, and information overload—when attempting to verify AI outputs against strict accounting standards [7]. When students' cognitive processing capacity is exceeded, they risk engaging in passive acceptance rather than active knowledge construction, leading to superficial learning and procedural errors in complex financial accounting tasks.

Despite growing interest in educational technology, empirical research examining how GenAI's pedagogical capacity and students' cognitive limitations interact to influence academic performance remains sparse, particularly within procedural accounting domains. The financial accounting cycle—spanning transaction analysis, journalization, ledger posting, worksheet preparation, and financial statement generation—demands both conceptual understanding and rigorous analytical precision.

To address this gap, this study applies Constructivist Learning Theory to evaluate how GenAI utilization (specifically ChatGPT) impacts student academic performance in financial accounting education, explicitly examining the interplay between pedagogical capacity as a learning facilitator and student cognitive limitations as a processing constraint. By doing so, this study contributes to academic literature by elucidating the constructivist mechanisms through which AI scaffolding either enhances or hinders deep domain learning, and offering empirical insights to help educators design balanced, ethically grounded AI integration strategies that mitigate student cognitive overload while maintaining academic rigor.

II. LITERATURE REVIEW

2.1 The Theoretical Foundation: Constructivist Learning Theory

Constructivist Learning Theory posits that learning is an active, dynamic process wherein individuals construct internal representations of knowledge through experiential engagement and environmental interaction. Central to this paradigm is Vygotsky's concept of the Zone of Proximal Development (ZPD), which asserts that optimal cognitive growth occurs when learners engage in tasks slightly beyond their independent capabilities with the assistance of a "More Knowledgeable Other" (MKO) [8]. In contemporary higher education, advanced technological systems—specifically Generative AI—increasingly act as artificial MKOs, offering dynamic digital scaffolding that assists students in navigating complex theoretical and procedural concepts [8].

2.2 Contextualizing the Financial Accounting Cycle

The financial accounting cycle constitutes a highly structured, sequential framework fundamental to business reporting and financial analysis. This cycle encompasses transaction identification and analysis, journalization, ledger posting across primary and subsidiary accounts, unadjusted trial balance preparation, worksheet compilation, financial statement generation, closing entries, and post-closing trial balance verification [9], [10], [11]. Because each stage demands mathematical accuracy, rule-bound logic, and professional judgment, the accounting cycle serves as a critical domain for evaluating technology-assisted learning and procedural verification.

2.3 Generative Artificial Intelligence and AI Literacy

Generative AI represents an advanced technological paradigm designed to emulate human reasoning and decision-making capabilities [3]. Engaging effectively with these tools requires AI literacy—a multidimensional set of competencies enabling individuals to critically evaluate, interact with, and ethically deploy AI technologies across academic and professional settings [12]. Despite its growing prominence in educational research, scholars emphasize that a standardized consensus regarding the measurement and operationalization of AI literacy remains elusive [13], [14].

2.4 Empirical Synthesis and Literature Gap

Empirical literature demonstrates a strong positive correlation between AI integration and academic achievement, showing that sufficient AI literacy significantly enhances learning outcomes and student performance [15], [16], [17], [18], [19], [20], [21]. Across diverse sectors, AI applications have proven transformative: optimizing programming instruction [22], streamlining operational workflows in accounting and auditing [23], [24], enhancing financial forecasting [25], and guiding ethical decision-making in healthcare [26], [27]. Furthermore, technology acceptance literature indicates that perceived usefulness, performance expectancy, user attitudes, trust, and effort expectancy drive behavioral intention and adoption across industries [28], [29], [30].

Despite these developments, current literature remains fragmented. Prior studies predominantly analyze general technology acceptance or isolated performance metrics, leaving a critical gap regarding how Generative AI interacts with domain-specific learning processes. Specifically, existing research lacks a comprehensive empirical model that simultaneously evaluates the dual roles of pedagogical capacity (as an instructional scaffold) and student cognitive limitations (as an information-processing constraint) on academic performance within financial accounting education.

III. METHODS

This study adopted a quantitative, explanatory research design to empirically examine the causal relationships among Generative AI (GenAI) utilization, pedagogical capacity, student cognitive limitations, and academic performance. Data

were collected using a purposive sampling technique at the Department of Accounting, Politeknik Negeri Bali (PNB). The target sample comprised undergraduate students enrolled across three vocational accounting study programs: D4 Managerial Accounting, D4 Tax Accounting, and D3 Accounting. To ensure data relevance, inclusion criteria strictly required participants to have active experience using GenAI tools—specifically ChatGPT—within their financial accounting coursework.

Primary data collection relied on a structured, self-administered questionnaire, supplemented by semi-structured interviews conducted both in person and via telephone, alongside official institutional documentation for demographic profiling. All latent constructs—comprising GenAI Use, Pedagogical Capacity, Student Cognitive Limitations, and Academic Performance—were operationalized using multi-item measurement scales evaluated on a 5-point Likert scale (ranging from 1 = strongly disagree / very poor to 5 = strongly agree / very good).

Statistical analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) executed through WarpPLS 8.0. The empirical evaluation followed a standard two-stage analytical procedure. First, the measurement model (outer model) was evaluated to establish construct validity through convergent and discriminant validity testing, alongside internal consistency reliability. Second, the structural model (inner model) was assessed to examine the hypothesized causal pathways, evaluate the model's explanatory power (R^2) and predictive relevance (Q^2), and verify path coefficient significance.

IV. Results and Discussion

4.1 Results

4.1.1 Sample Characteristics

The final research sample comprised 150 undergraduate accounting students ($N = 150$) displaying diverse demographic backgrounds across academic levels and study specializations. In terms of gender distribution, the sample was predominantly female, representing 89% ($n = 134$) of respondents, while male students constituted 11% ($n = 16$). Regarding academic standing, second-semester students formed the largest cohort at 42% ($n = 63$), followed by sixth-semester students at 31% ($n = 46$) and fourth-semester students at 27% ($n = 41$). Across study programs, Managerial Accounting represented the largest proportion of participants at 35% ($n = 52$), followed by Tax Accounting at 25% ($n = 37$), General Accounting at 23% ($n = 35$), and Digital Business Accounting at 17% ($n = 26$).

The empirical evaluation of the PLS-SEM path model was conducted in two sequential phases: the evaluation of the measurement model (outer model) followed by the structural model (inner model).

4.1.2 Measurement Model Evaluation (Outer Model)

Table 1. Measurement Model Evaluation

Construct	Indicator	Loadings	AVE	Sq. Rts. of AVEs	CR	CA	VIF
Generative (AI)	AI1Using AI for understanding accounting concepts	0.769	0.612	0.782	0.863	0.787	1.341
	AI2 Using AI for completing academic tasks	0.769					
	AI3 Using AI to enhance learning efficiency	0.743					
	AI4 Frequency of AI use for learning purposes	0.844					
Academic Performance (AP)	AP1 Improvement in understanding accounting material	0.763	0.622	0.789	0.868	0.797	1.191
	AP2 Quality of assignment completion	0.832					
	AP3 Academic grade achievement	0.790					
	AP4 Academic self-confidence	0.769					
Pedagogical Capacity (PC)	PC1 Ability to integrate AI into the learning process	0.731	0.650	0.806	0.847	0.729	1.470
	PC2 Critical utilization of generative AI	0.842					
	PC3 Ability to evaluate information accuracy	0.841					
Cognitive Limitations (CL)	CL1 Cognitive overload during AI interaction	0.681	0.598	0.773	0.816	0.660	1.051
	CL2 Reduction in critical thinking capacity	0.828					
	CL3 Cognitive dependence on AI	0.802					

For the reflective first-order measurement model, psychometric properties were evaluated through convergent validity, discriminant validity, and internal consistency reliability. Convergent validity was established by evaluating the indicator outer loadings and Average Variance Extracted (AVE) metrics across all latent constructs. As shown in the table, nearly all indicator outer loadings exceeded the standard threshold of 0.70 (ranging from 0.731 to 0.844), demonstrating high item-level reliability. Although indicator CL1 yielded an outer loading of 0.681, it was retained because the AVE for Cognitive Limitations (0.598) comfortably surpassed the required 0.50 benchmark without compromising measurement quality. Furthermore, the AVE values for all latent variables ranged from 0.598 to 0.650—specifically, Generative AI (0.612), Academic Performance (0.622), Pedagogical Capacity (0.650), and Cognitive Limitations (0.598)—confirming that each construct explains well over 50% of the variance in its associated indicators, thus firmly establishing adequate convergent validity.

Discriminant validity was evaluated using Cross-Loadings, the Fornell-Larcker Criterion, and the Heterotrait-Monotrait (HTMT) ratio. Each indicator loaded higher on its intended latent construct than on any other construct in the model. The square roots of the AVE values for Generative AI (0.782), Academic Performance (0.789), Pedagogical Capacity (0.806), and Cognitive Limitations (0.773) all exceeded the baseline threshold of 0.50 and were strictly greater than the correlations between latent variables. All HTMT ratios remained well below the recommended conservative threshold of 0.90. These metrics confirm that each construct shares greater variance with its assigned indicators than with any other construct in the model, thereby firmly establishing discriminant validity.

Internal consistency reliability was evaluated using Composite Reliability (CR) and Cronbach's Alpha (α) coefficients across all measurement constructs. As presented in the table, the CR values ranged from 0.816 to 0.868—specifically, Generative AI (0.863), Academic Performance (0.868), Pedagogical Capacity (0.847), and Cognitive Limitations (0.816)—all comfortably exceeding the standard benchmark of 0.70. Additionally, Cronbach's Alpha values for Generative AI (0.787), Academic Performance (0.797), and Pedagogical Capacity (0.729) surpassed the recommended 0.70 threshold, while Cognitive Limitations yielded a value of 0.660, which remains within the acceptable range of 0.60 to 0.70 for exploratory empirical contexts. Together, these findings demonstrate high internal consistency and satisfactory construct reliability for the proposed model.

4.1.3 Structural Model Evaluation (Inner Model)

Lateral collinearity was evaluated using Variance Inflation Factor (VIF) metrics to ensure that multicollinearity does not distort the structural estimations. As presented in the table, the VIF values for all latent constructs ranged from 1.051 to 1.470—specifically, Generative AI (1.341), Academic Performance (1.191), Pedagogical Capacity (1.470), and Cognitive

Limitations (1.051). All VIF metrics are well below the conservative threshold of 3.3 (as well as the standard cutoff of 5.0), confirming the absence of collinearity issues within the structural model.

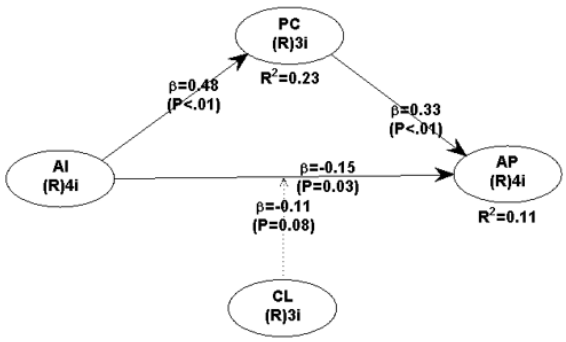


Fig. 1 Path model with path coefficients and p-values

The structural path evaluation revealed significant direct relationships across the primary hypothesized pathways. Generative AI utilization exhibited a strong, positive, and statistically significant direct effect on pedagogical capacity ($\beta = 0.48, p < 0.01$). In turn, pedagogical capacity exerted a positive and statistically significant impact on student academic performance ($\beta = 0.33, p < 0.01$). Intriguingly, the direct pathway from Generative AI utilization to academic performance was negative yet statistically significant ($\beta = -0.15, p = 0.03$), indicating that unmediated or raw reliance on AI tools may inadvertently impair learning outcomes. Regarding the indirect pathways, pedagogical capacity functioned as a vital mediating mechanism between Generative AI usage and academic performance. The calculated indirect effect through pedagogical capacity (AI → PC → AP) yielded a positive standardized coefficient ($\beta_{\text{indirect}} \approx 0.16, p < 0.01$). Given that the direct effect ($\beta = -0.15$) and indirect effect ($\beta \approx 0.16$) carry opposing signs, the empirical model demonstrates a competitive mediation (or inconsistent mediation) pattern. This finding highlights that Generative AI adoption only produces favorable academic results when channeled through enhanced pedagogical capacity. The hypothesized moderating effect of student cognitive limitations on the relationship between Generative AI usage and academic performance was also examined. The interaction term (CL × AI → AP) produced a negative coefficient ($\beta = -0.11, p = 0.08$), which failed to reach statistical significance at the standard threshold ($\alpha = 0.05$).

In terms of explanatory power, Generative AI usage accounted for 23% of the variance in pedagogical capacity ($R^2 = 0.23$), whereas the overall structural model explained 11% of the total variance in academic performance ($R^2 = 0.11$). Practical relevance was evaluated using Cohen's f^2 effect size metrics. As presented in the table, the path from Generative AI usage to pedagogical capacity yielded the largest effect size ($f^2 = 0.230$), indicating a medium-to-large practical impact. Pedagogical capacity also demonstrated a substantial contribution to academic performance ($f^2 = 0.130$), approaching the medium threshold. Conversely, the direct path from Generative AI usage to academic performance exhibited a small effect size ($f^2 = 0.042$). Finally, the moderating effect of cognitive limitations (CL × AI → AP) produced a negligible effect size ($f^2 = 0.018 < 0.02$), confirming its lack of practical significance in the structural model.

The out-of-sample predictive capacity of the structural model was evaluated using Stone-Geisser's Q^2 coefficients. In PLS-SEM analysis, a Q^2 value strictly exceeding zero ($Q^2 > 0$) confirms that the model possesses satisfactory predictive relevance for a given endogenous construct, with values of 0.02, 0.15, and 0.35 denoting small, medium, and large predictive relevance, respectively. As depicted in the statistical output, both endogenous constructs yielded Q^2 metrics well above the threshold: Pedagogical Capacity (PC) recorded a Q^2 of 0.232, and Academic Performance (AP) achieved a Q^2 of 0.196. These results demonstrate that the empirical model exhibits medium out-of-sample predictive power and robust predictive validity across all target constructs.

4.2 Discussion

The empirical findings reveal a compelling structural paradox in higher accounting education: while direct reliance on Generative AI (GenAI) exerts a statistically significant negative impact on student academic performance ($\beta = -0.15, p = 0.03$), its indirect effect through pedagogical capacity is strongly positive ($\beta_{\text{indirect}} \approx 0.16, p < 0.01$). This structural configuration establishes a competitive mediation (inconsistent mediation) pattern. Unmediated or raw utilization of GenAI acts as a double-edged sword. When students deploy GenAI merely as an automated answer-generator to complete assignments, it triggers cognitive offloading—a process wherein learners bypass the necessary cognitive effort required to master complex accounting principles, debits and credits reconciliation, or financial reporting frameworks. Consequently, direct AI reliance degrades deep conceptual learning, yielding poorer academic outcomes

($f^2 = 0.042$). Conversely, when GenAI adoption is filtered through and mediated by pedagogical capacity, the technology transforms from a passive shortcut into a catalyst for academic excellence. Generative AI usage strongly predicts pedagogical capacity ($\beta = 0.48, p < 0.01$), capturing the largest effect size in the structural model ($f^2 = 0.230$). In turn, heightened pedagogical capacity significantly drives academic performance ($\beta = 0.33, p < 0.01, f^2 = 0.130$). This mechanism proves that the technology itself does not inherently degrade learning; rather, the absence of pedagogical structure and evaluative capability creates negative learning outcomes.

These empirical results align directly with Constructivist Learning Theory and Vygotsky's Zone of Proximal Development (ZPD). Within this theoretical framework, GenAI functions as a digital "More Knowledgeable Other" (MKO) that provides continuous, adaptive scaffolding. However, software-driven scaffolding is inert unless the learner possesses the pedagogical capacity to engage with it interactively. Pedagogical capacity—defined by a student's ability to integrate AI critically, evaluate output accuracy, and verify domain-specific accounting rules—serves as the bridge that elevates a student from their actual developmental level to their potential developmental level. Without pedagogical capacity, students treat GenAI outputs as absolute truth, falling prey to algorithmic hallucinations and over-simplifications. When pedagogical capacity is actively exercised, GenAI serves as an interactive Socratic partner: students prompt the tool to explain intricate tax regulations or managerial accounting variances, evaluate the response against theoretical rules, and refine their own conceptual understanding. Thus, pedagogical capacity neutralizes the direct negative suppression effect of GenAI, converting raw technology adoption into higher academic performance ($R^2 = 0.11, Q^2 = 0.196$).

The interaction term representing the moderating role of student cognitive limitations (CL × AI → AP) yielded a negative coefficient ($\beta = -0.11, p = 0.08$) with a negligible effect size ($f^2 = 0.018$). At the standard significance threshold ($\alpha = 0.05$), cognitive limitations do not significantly moderate the path between GenAI usage and academic performance. This finding suggests that while cognitive overload and cognitive dependence are recognized challenges in digital learning environments, their influence is secondary to the primary mediating force of pedagogical capacity. In essence, strong pedagogical capacity buffers against cognitive strain, rendering the direct moderating influence of cognitive limitations statistically non-significant. Furthermore, the out-of-sample predictive relevance metrics ($Q^2 = 0.232$ for Pedagogical Capacity; $Q^2 = 0.196$ for Academic Performance) confirm that the conceptual framework holds solid predictive power. These values demonstrate that the model successfully predicts performance outcomes beyond sample-specific estimations, offering a reliable blueprint for technical and vocational higher education institutions.

The empirical evidence offers clear guidance for academic administrators and educators in accounting programs. Banning GenAI in accounting education is both impractical and counterproductive. Given that direct AI use without guidance negatively impacts academic performance, educators must actively structure AI usage through guided learning activities. Accounting curricula should explicitly teach prompt engineering, auditing of AI-generated financial analyses, and fact-checking against official accounting standards (e.g., IFRS/PSAK). Developing students' capacity to critically evaluate AI output addresses the root cause of the direct negative effect ($\beta = -0.15$). Traditional homework assignments that test lower-order recall or routine calculations are highly vulnerable to unmediated AI offloading. Educators should adopt authentic assessments—such as oral defense examinations, real-world case studies, and critical comparison essays evaluating human vs. AI financial analysis—that require high pedagogical engagement.

V. CONCLUSION

This study provides empirical clarity on the nuanced relationship between Generative AI (GenAI) utilization and academic performance in vocational accounting education by establishing the critical mediating role of pedagogical capacity. The findings demonstrate a competitive mediation paradox: while direct, unguided reliance on GenAI exerts a statistically significant negative impact on student performance ($\beta = -0.15, p = 0.03$), the technology becomes highly beneficial when channeled through pedagogical capacity ($\beta_{\text{indirect}} \approx 0.16, p < 0.01$). Furthermore, student cognitive limitations do not significantly moderate the direct link between GenAI and performance at the standard significance level ($\beta = -0.11, p = 0.08$), indicating that cognitive strain is secondary to the primary scaffolding provided by pedagogical capability. Ultimately, the empirical model proves that GenAI adoption itself does not inherently impair accounting education; rather, academic outcomes depend on whether students possess the evaluative and critical capacity required to transform automated outputs into deep conceptual learning.

The theoretical and practical implications of this study extend directly to accounting curriculum design and higher education policy. Theoretically, the findings expand Constructivist Learning Theory and Vygotsky's Zone of Proximal Development (ZPD) by demonstrating that GenAI functions as a digital "More Knowledgeable Other" whose scaffolding efficacy is contingent upon the student's active pedagogical capacity. Practically, higher education institutions must abandon ineffective blanket bans on AI and instead transition toward structured pedagogical integration. Accounting faculties should embed formal AI literacy modules—focusing on prompt engineering, critical verification of AI outputs against official accounting standards (e.g., IFRS/PSAK), and algorithmic auditing—into core coursework. Furthermore,

assessment frameworks must shift away from routine, calculation-heavy homework that encourages passive cognitive offloading toward authentic higher-order evaluations, such as case study defenses, oral examinations, and comparative human-versus-AI financial report analyses.

Several methodological and contextual limitations must be acknowledged when interpreting these results. First, the cross-sectional design and reliance on a sample of $N = 150$ undergraduate students from a single vocational institution (Politeknik Negeri Bali) restrict the ability to draw definitive causal conclusions or generalize findings across non-vocational universities and different geographic regions. Second, the data rely on self-reported survey instruments to capture students' cognitive limitations and perceived academic performance, which may introduce subjective reporting bias or social desirability bias. Third, the structural model examined a bounded set of variables within accounting education; thus, extraneous factors such as individual technological self-efficacy, specific GenAI platform variations (e.g., ChatGPT vs. Claude), instructor teaching styles, and institutional AI policies were not explicitly controlled for in the empirical analysis. To build upon these findings, future scholarship should adopt longitudinal or experimental research designs—such as randomized pre-test/post-test control group interventions—to observe how student pedagogical capacity develops over time under different AI-assisted learning frameworks. Researchers are also encouraged to expand the empirical scope by gathering multi-institutional and cross-disciplinary data across various business and technical domains to enhance model generalizability. Additionally, future studies should incorporate objective measurement tools, such as actual Grade Point Averages (GPA), standardized accounting competency test scores, or Learning Management System (LMS) clickstream analytics, alongside self-reported instruments. Finally, exploring additional contextual variables, such as instructor AI readiness, ethical mindset, and task complexity, will yield a more holistic understanding of how Generative AI can be optimized for academic success.

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