

AI Literacy and Student Self-Efficacy in Accounting-Oriented Financial Management Education

Diana Puspitasari^{1*}, Sugeng Wahyudi¹, Irine Rini Demi Pangestuti¹, Agus Dwianto²

¹Faculty of Economics and Business, Universitas Diponegoro, Semarang, Central Java, Indonesia, 50275, Email ID: dianapuspitasari718@dsn.dinus.ac.id, ORCID ID: 0000-0002-2831-1340, Scopus Author ID: 57226074346

¹Faculty of Economics and Business, Universitas Diponegoro, Semarang, Central Java, Indonesia, 50275, Email ID: sug_w@yahoo.com, ORCID ID: 0000-0003-2889-7123, Scopus Author ID: 57189356898

¹Faculty of Economics and Business, Universitas Diponegoro, Semarang, Central Java, Indonesia, 50275, Email ID: irenerinidp1960@gmail.com, ORCID ID: 0000-0003-3008-0972, Scopus Author ID: 57195474632

²Department of Data Analytics and Computational Research, Inovasi Analisis Data, Banyumanik, Semarang, Indonesia, 50261, Email ID: agusdwianto90@gmail.com, ORCID ID: 0009-0009-3681-048X, Scopus Author ID: 57195054771

HOW TO CITE:

Diana Puspitasari, Sugeng Wahyudi, Irine Rini Demi Pangestuti, Agus Dwianto (2026). AI Literacy and Student Self-Efficacy in Accounting-Oriented Financial Management Education. International Journal of Special Education, 41(7s), 1434-1454

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.
Open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

ABSTRACT:

Artificial intelligence is transforming accounting and financial management education by changing the way students access explanations, validate calculations and hone their financial reasoning skills. This study investigates student self-efficacy in AI-driven financial learning using an innovative accounting-focused survey method. The examination of motivation and self-efficacy is informed by theories such as Social Cognitive Theory, Self-Determination Theory, and Experiential Learning Theory. The focus of this examination is the impact of AI literacy, perceived support for AI learning, readiness for digital financial education, and anxiety about AI accounting technology. The findings suggest that AI literacy, perceived support for AI learning and readiness for digital financial education increase students' confidence in applying AI to accounting and financial tasks, whereas anxiety about AI reduces confidence and motivation. Furthermore, academic motivation is found to mediate the impact of AI-related learning conditions on self-efficacy. This research contributes to the fields of accounting education and educational technology by providing a discipline-specific framework that explains how students can develop confidence, motivation, and responsible skills in AI-supported financial management. The survey method presented here provides a foundation for developing future curricula, AI literacy programs, and innovative teaching strategies in accounting and finance education.

Keywords: AI Literacy; Financial Management Education; Student Self-Efficacy; Academic Motivation; Accounting Education.

Introduction

The field of artificial intelligence (AI) is exerting a rapid and profound influence on higher education, reshaping how students access explanations, develop ideas, receive feedback,

and engage with complex disciplinary tasks. In educational settings, the role of AI has evolved beyond that of a mere tool for automated tutoring or learning analytics. It is increasingly recognized as an educational partner that

facilitates reasoning, problem-solving, writing, assessment preparation, and self-directed learning (Chan & Hu, 2023; Crompton & Burke, 2023; Jin et al., 2023; Murtono & Prayitno, 2025; Ryani Kusumawati, 2024). This shift is particularly noteworthy in accounting and financial management education, where students are required to interpret financial data, assess decision options, and apply conceptual knowledge to uncertain business scenarios. As AI tools become integrated into learning environments, it is imperative to shift the focus from mere acceptance of AI by students to their ability to use AI in a critical, ethical, and confident manner to enhance their disciplinary skills.

The financial management curriculum should extend beyond basic procedural skills. It's crucial for students to develop competencies in budgeting, forecasting, investment analysis, reading financial statements, cost-benefit evaluations, and managerial decision-making. Recent studies in accounting education indicate that generative AI tools can assist in answering assessment questions and promote student learning. Nonetheless, these tools raise concerns about accuracy, academic integrity, overreliance on technology, and the possible erosion of independent reasoning (Haugland Sundkvist & Kulset, 2024; Wood et al., 2023). In higher education assessments, worries also exist regarding AI's potential for personalized feedback versus issues of authenticity, transparency, and fairness (Qu et al., 2025; Xia et al., 2024). Thus, AI-enabled financial management education should be seen as more than just technology-enhanced learning; it should foster students' digital skills, financial judgment, ethical awareness, and confidence (Arifah & Rizki Nugraha, 2024).

In this context, student self-efficacy is vital, as it indicates their confidence in performing academic tasks within specific learning settings. In AI-enhanced education, self-efficacy extends beyond confidence in digital tools to encompass students' perceived ability to evaluate AI outputs, correct mistakes, follow disciplinary standards, and uphold academic integrity. Recent research has begun to treat artificial intelligence self-

efficacy as a quantifiable concept in education, emphasizing students' confidence in understanding and applying AI effectively (Y.-Y. Wang & Chuang, 2024). As demonstrated in other studies (F. Wang et al., 2023), the use of AI in higher education can affect students' self-efficacy, creativity, and learning outcomes. However, most current literature remains broad rather than discipline-specific. In accounting and financial management education, it is crucial to link students' self-efficacy to their skills in applying AI to financial analysis, interpretation, and decision-making.

A key gap in current research is the lack of a specialized survey tool to measure student self-efficacy in AI-enhanced financial management education. Although studies have made notable progress in assessing AI literacy, AI skills, readiness for online learning, and perceptions of generative AI (Cheng et al., 2025; Delcker et al., 2024; Lintner, 2024; Ng et al., 2024; Ning et al., 2025), these assessments mainly focus on broad AI awareness, digital competencies, or perceived usefulness. They do not specifically measure students' competence in applying AI to accounting-related financial tasks. Furthermore, research on AI applications such as ChatGPT in accounting education has largely focused on student performance and perceptions. A comprehensive survey model that combines AI literacy, pedagogical support, digital financial readiness, technology anxiety, academic motivation, and self-efficacy within accounting education has not yet been established (Abeysekera, 2024; Haugland Sundkvist & Kulset, 2024; Wood et al., 2023).

This discrepancy is especially significant in financial management and accounting education because students' confidence in AI-assisted learning depends on their ability to connect AI outputs with core disciplinary reasoning, financial skills, and pedagogical understanding. Developing strong AI literacy enables students to assess the relevance, accuracy, and limitations of AI-generated explanations in areas such as budgeting, forecasting, capital budgeting, and financial analysis. How AI learning support is used is crucial—it should serve as a structured

scaffold for understanding financial concepts or be used as a shortcut for assignments. Students' readiness for digital-financial learning also influences their ability to use AI with spreadsheets, accounting systems, and financial analysis tools. Conversely, anxiety about AI accounting technology can diminish students' willingness to critically evaluate AI outputs. Therefore, maintaining academic motivation is vital, as students need to see AI-supported learning as a way to strengthen their financial management skills, accounting judgment, and career-focused analytical abilities (Chan & Zhou, 2023; F. Wang et al., 2023). Students' preparedness for digital-financial education also impacts their capability to operate AI-driven tools like spreadsheets, accounting systems, and financial analysis software (Dwianto et al., 2025; Septiani et al., 2026).

This study aims to develop a new survey approach focused on accounting to assess student self-efficacy in AI-driven financial management education. It explores how AI literacy, perceived learning support, digital-financial readiness, and AI-accounting anxiety influence students' motivation and confidence in this field. By addressing this, the research contributes to the accounting education and educational technology literature by developing a discipline-specific framework for understanding how students develop confidence, motivation, and responsible skills in AI-enhanced financial management learning.

Literature Review

Theoretical Foundation

Bandura's Social Cognitive Theory serves as the foundational framework, emphasizing self-efficacy as learners' belief in their capacity to successfully organize and execute academic tasks (Bandura, 1986; Bandura et al., 1999). In AI-enhanced financial management education, this self-efficacy pertains not only to students' confidence in using AI tools but also to their ability to assess AI-generated financial explanations, identify reasoning errors, and apply accounting principles responsibly. Through mastery experiences, vicarious learning, social

encouragement, and emotional states, students gain confidence in using AI for activities such as budgeting, forecasting, ratio analysis, capital budgeting, working capital decisions, and interpreting financial reports. Recent research indicates that AI competence and institutional AI capability positively influence students' self-efficacy, creativity, and learning outcomes (F. Wang et al., 2023; Y.-Y. Wang & Chuang, 2024).

Self-Determination Theory explains that providing autonomy, constructive feedback on competence, and engaging learning experiences can boost Academic Motivation (Deci & Ryan, 1985; Ryan & Deci, 2000). The present study indicates that Academic Motivation serves as a mediator between AI-related learning conditions and students' confidence in managing financial concepts. Kolb's Experiential Learning Theory also supports this teaching method, emphasizing that AI-driven education should involve financial cases, simulations, reflection, validation, and decision-making rather than passive recall of answers (Kolb, 1984). Prior research shows that students' motivation to learn AI is shaped by supportive surroundings, perceived usefulness, and expectancy-value beliefs (Chan & Zhou, 2023; F. Wang et al., 2023).

Learning Antecedents of Student Self-Efficacy in AI-Driven Financial Management

Student self-efficacy in AI-driven financial management depends on learning conditions that help students understand, use, and evaluate AI in accounting tasks. According to Social Cognitive Theory, AI literacy mirrors mastery experience, as students gain confidence when they can assess AI's capabilities, limitations, and ethical issues (Chee et al., 2025; Ng et al., 2024).

Support for AI learning boosts confidence through scaffolding, feedback, and guided problem-solving, enabling students to better grasp complex financial concepts (Crompton & Burke, 2023; Jin et al., 2023). Readiness for digital financial learning also enhances self-efficacy by enabling students to integrate AI with spreadsheets, accounting systems, and financial analysis tools (Delcker et al., 2024; Van Wart et al., 2020). However, anxiety about AI-accounting

technology may reduce self-efficacy, as uncertainty, ethical concerns, and fear of errors can discourage students from engaging critically with AI-supported accounting and finance tasks (Arifah & Rizki Nugraha, 2024; Haugland Sundkvist & Kulset, 2024; Lund et al., 2024; Qu et al., 2025). Therefore, the following hypotheses are proposed:

- H1. AI Literacy in Financial Education positively influences Student Self-Efficacy in AI-Driven Financial Management.
- H2. Perceived AI Learning Support positively influences Student Self-Efficacy in AI-Driven Financial Management.
- H3. Digital-Financial Learning Readiness positively influences Student Self-Efficacy in AI-Driven Financial Management.
- H4. AI-Accounting Technology Anxiety negatively influences Student Self-Efficacy in AI-Driven Financial Management.

Learning Antecedents of Academic Motivation in AI-Enhanced Finance Learning

The concept of academic motivation in the context of AI-enhanced finance learning refers to students' propensity to invest effort, maintain engagement, and view AI-supported learning as a valuable asset for developing competence in accounting and financial management. The integration of AI literacy into educational curricula has been shown to enhance students' motivation. This is because students who understand the functions, limitations, and ethical implications of AI are more likely to utilize AI as a disciplined learning resource rather than as a mere shortcut (Almatrafi et al., 2024; Lintner, 2024).

The provision of feedback, scaffolding, and alternative explanations by artificial intelligence (AI) systems has been shown to enhance students' motivation, thereby facilitating the comprehension of complex financial concepts (Crompton & Burke, 2023; Xia et al., 2024). The degree of individuals' digital literacy in finance can further enhance motivation, given that prepared students have the capacity to integrate AI with digital platforms, spreadsheets, and

finance-related tasks more effectively (Abuhassna et al., 2020; Almatrafi et al., 2024; Mah & Groß, 2024; Septiani et al., 2026). On the other hand, anxiety about AI-based accounting technology can lower motivation by portraying AI-supported learning as uncertain, ethically questionable, or difficult to manage (O'Dea, 2024; Qu et al., 2025). Previous research (Chan & Zhou, 2023; F. Wang et al., 2023) has shown that students' motivation to learn with AI depends on perceived learning benefits, supportive settings, and expectancy-value beliefs. Based on these findings, the following hypotheses are proposed:

- H5. AI Literacy in Financial Education positively influences Academic Motivation in AI-Enhanced Finance Learning.
- H6. Perceived AI Learning Support positively influences Academic Motivation in AI-Enhanced Finance Learning.
- H7. Digital-Financial Learning Readiness positively influences Academic Motivation in AI-Enhanced Finance Learning.
- H8. AI-Accounting Technology Anxiety negatively influences Academic Motivation in AI-Enhanced Finance Learning.

Academic Motivation and Student Self-Efficacy in AI-Driven Financial Management

Academic motivation plays a crucial role in shaping student self-efficacy, reflecting their willingness to exert effort, persist with challenging tasks, and utilize AI-supported learning to enhance their skills.

In AI-based financial management education, motivated students tend to explore AI explanations, verify calculations, compare solutions, and connect learning to future finance applications. Studies indicate that motivation in tech-supported learning is influenced by perceived learning value, a supportive environment, and students' self-regulation of engagement (Lan & Hew, 2020; Mendoza et al., 2023; F. Wang et al., 2023). Student self-efficacy in AI-driven financial management depends not only on awareness of AI tools but also on their

motivation to understand, assess, and apply AI outputs in line with disciplinary standards. When students see AI-supported activities as relevant to budgeting, forecasting, financial analysis, and decision-making grounded in accounting principles, they are more confident in using AI responsibly. This aligns with evidence linking AI skills and self-efficacy to students' confidence, creativity, and academic performance (Gašević et al., 2023; Y.-Y. Wang & Chuang, 2024). Consequently, the following hypothesis is proposed:

H9. Academic Motivation in AI-Enhanced Finance Learning positively influences Student Self-Efficacy in AI-Driven Financial Management.

Mediating Role of Academic Motivation in AI-Enhanced Finance Learning

Academic motivation might clarify how AI-related learning environments influence students' confidence in AI-driven financial education. AI literacy can boost motivation by helping students understand the instructional benefits, limitations, and ethical considerations of AI in finance, thereby enhancing their confidence in applying AI to accounting-related financial tasks (Almatrafi et al., 2024; Chee et al., 2025). Perceived support in AI learning may also increase motivation when AI offers scaffolding, feedback, and alternative explanations that promote deeper engagement with financial concepts (Crompton & Burke, 2023; Edwards et al., 2025). Similarly, readiness for digital financial learning can indirectly improve self-efficacy, as students familiar with digital platforms, spreadsheets, and AI-supported financial tools are more likely to view AI-enhanced learning as feasible and meaningful (Joosten & Cusatis, 2020; Wei & Chou, 2020).

Conversely, anxiety about AI-accounting technology may reduce motivation by making AI-supported accounting and finance learning appear uncertain, ethically risky, or difficult to control (O'Dea, 2024; Qu et al., 2025). When

motivation declines, students may become less willing to verify AI-generated financial outputs, persist in complex problem-solving, or apply disciplinary judgment. Prior research shows that motivation and self-efficacy in AI-supported learning are shaped by perceived learning value, supportive environments, and students' confidence in using AI responsibly (Mendoza et al., 2023; F. Wang et al., 2023; Y.-Y. Wang & Chuang, 2024). Accordingly, the following hypotheses are proposed:

H10. Academic Motivation mediates the relationship between AI Literacy and Student Self-Efficacy.

H11. Academic Motivation mediates the relationship between Perceived AI Learning Support and Student Self-Efficacy.

H12. Academic Motivation mediates the relationship between Digital-Financial Learning Readiness and Student Self-Efficacy.

H13. Academic Motivation mediates the relationship between AI-Accounting Technology Anxiety and Student Self-Efficacy.

Conceptual Framework

As illustrated in Figure 1, the proposed conceptual model of AI-driven financial management education is as follows. The proposed theoretical framework positions AI Literacy in Financial Education, Perceived AI Learning Support, Digital-Financial Learning Readiness, and AI-accounting technology anxiety as learning antecedents of Student Self-Efficacy in AI-Driven Financial Management. The incorporation of academic motivation in AI-enhanced finance learning as a mediating mechanism provides a comprehensive explanation of how AI-related learning conditions shape students' confidence in using AI for accounting-oriented financial management tasks.

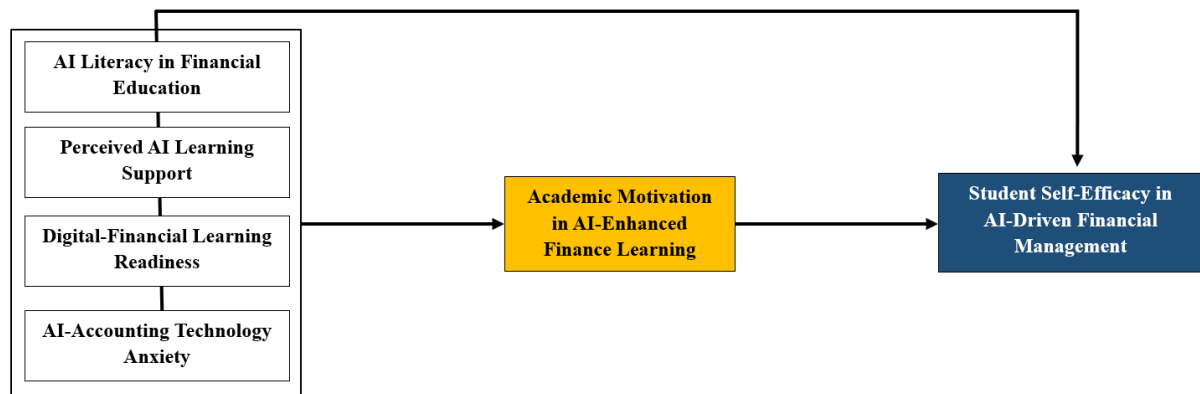


Figure 1. Conceptual Model of AI-Driven Financial Management Education

Methodology

Design

This study utilizes a quantitative survey to assess student self-efficacy in AI-powered financial management education. It is based on Social Cognitive Theory, which describes self-efficacy as confidence in learning influenced by mastery experiences, vicarious learning, social encouragement, and emotional states (Bandura, 1986). Additionally, Self-Determination Theory supports this model by highlighting how autonomy, competence feedback, and meaningful learning experiences boost students' motivation in AI-enhanced settings (Deci & Ryan, 1985; Murtono & Prayitno, 2025; Ryan & Deci, 2000). The pedagogical framework is further grounded in Experiential Learning Theory, as AI-supported financial management requires students to analyze financial cases, interpret AI insights, verify calculations, apply accounting principles, and reflect on decisions (Kolb, 1984). Studies on technology-enhanced learning also emphasize the importance of AI literacy, perceived learning support, readiness, and anxiety as key factors influencing students' engagement and confidence in learning (Chan & Hu, 2023; Delcker et al., 2024; Ng et al., 2024; F. Wang et al., 2023; Y.-Y. Wang & Chuang, 2024).

Participants/Sample

The research focuses on undergraduate students studying Accounting and Financial Management who have used AI tools during their coursework. These students are important because they are

expected to develop skills such as financial reasoning, interpreting accounting data, budgeting, forecasting, and decision-making within AI-supported learning environments. Based on Social Cognitive Theory, the study emphasizes students' self-efficacy in using AI to assess financial explanations, verify calculations, and apply accounting principles responsibly. Participants are bachelor's students familiar with generative AI and AI-assisted tools like ChatGPT, Microsoft Copilot, Gemini, Perplexity, AI features in spreadsheets, AI-based accounting software, and financial analysis tools. Existing research indicates that AI literacy, learning readiness, and self-efficacy are vital for effective technology-enhanced learning (Chan & Hu, 2023; Delcker et al., 2024; Ng et al., 2024; F. Wang et al., 2023; Y.-Y. Wang & Chuang, 2024). Additionally, accounting education research highlights both benefits and potential risks of generative AI (Haugland Sundkvist & Kulset, 2024; Wood et al., 2023; Xia et al., 2024).

Instruments

The research instrument was developed as a structured questionnaire designed to assess students' perceptions of AI-driven financial management education. All constructs were operationalized using reflective indicators adapted from prior studies on artificial intelligence literacy, AI-supported learning, digital readiness, technology anxiety, academic motivation, accounting education, and AI self-efficacy. Items related to AI literacy in financial

education were adapted from research on AI literacy and ethical AI competence (Almatrafi et al., 2024; Chee et al., 2025; Lintner, 2024; Ng et al., 2024). Meanwhile, the perceived AI learning support construct was based on earlier research on generative AI, self-regulated learning, and AI-supported instructional scaffolding (Chan & Hu, 2023; Crompton & Burke, 2023; Jin et al., 2023; Xia et al., 2024). The Digital-Financial Learning Readiness concept was inspired by studies on AI competence (Delcker et al., 2024), online learning readiness (Darsono et al., 2026; Van Wart et al., 2020), and digital learning engagement (Abuhassna et al., 2020; Joosten & Cusatis, 2020; Mah & Groß, 2024).

Research has highlighted the phenomenon of AI-accounting technology anxiety, focusing on emotional tension, ethical concerns, and uncertainty in AI-supported higher education and accounting learning (Haugland Sundkvist & Kulset, 2024; Lund & Naheem, 2024; Qu et al., 2025; Wood et al., 2023). The concept of Academic Motivation in AI-Enhanced Finance Learning is grounded in studies on expectancy-value beliefs, motivation in AI learning, and skill development (Chan & Zhou, 2023; Mendoza et al., 2023; F. Wang et al., 2023). Likewise, Student Self-Efficacy in AI-Driven Financial Management draws from research on AI self-efficacy, AI capabilities, and related learning in accounting (Wang & Chuang, 2024; Wang et al., 2023; Abeysekera, 2024; Sundkvist & Kulset, 2024). Measurements were conducted using a five-point Likert scale from 1 = strongly disagree to 5 = strongly agree. For detailed information on

measurement items, construct codes, scales, and sources, see Appendix A, Table A.1.

Data Analysis

The study used variance-based structural equation modeling to evaluate measurement quality and examine relationships among AI literacy, AI learning support, digital-financial readiness, AI anxiety related to accounting technology, academic motivation, and student self-efficacy. Data screening was performed prior to testing indicator reliability, internal consistency, convergent validity, and discriminant validity, using measures including outer loadings, Cronbach's alpha, composite reliability, AVE, and HTMT. The structural model was assessed for collinearity, path coefficients, R^2 , effect size, predictive relevance, bootstrapping, and specific indirect effects, following PLS-SEM guidelines (Hair, Black, et al., 2019; Hair, Risher, et al., 2019; Shmueli et al., 2019).

Results

Respondent

The final sample consisted of 320 students selected through purposive stratified sampling across cities, study programs, and semesters. As shown in Table 1, most respondents were aged 21–22 years (48.1%), female (55.6%), and enrolled in Financial Management programs (54.4%). The majority were in semesters 5–6 (52.5%), had 6–12 months of AI learning experience (39.4%), primarily used ChatGPT (56.9%), and accessed AI tools 3–5 times per week (40.0%).

Table 1. Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage
Age	18–20 years	86	26.90%
Age	21–22 years	154	48.10%
Age	23–24 years	58	18.10%
Age	>24 years	22	6.90%
Gender	Female	178	55.60%
Gender	Male	142	44.40%

Characteristic	Category	Frequency	Percentage
Study Program	Accounting	146	45.60%
Study Program	Financial Management	174	54.40%
Semester	3–4	76	23.80%
Semester	5–6	168	52.50%
Semester	7–8	76	23.80%
AI Learning Experience	<6 months	88	27.50%
AI Learning Experience	6–12 months	126	39.40%
AI Learning Experience	>12 months	106	33.10%
Main AI Tool Used	ChatGPT	182	56.90%
Main AI Tool Used	Microsoft Copilot	54	16.90%
Main AI Tool Used	Gemini	42	13.10%
Main AI Tool Used	AI-based accounting/finance software	28	8.80%
Main AI Tool Used	Other AI tools	14	4.40%
Frequency of AI Use	Occasional/monthly	30	9.40%
Frequency of AI Use	1–2 times/week	74	23.10%
Frequency of AI Use	3–5 times/week	128	40.00%
Frequency of AI Use	Daily	88	27.50%

Descriptive Statistics

Table 2. Descriptive statistics reveal consistent measurement of all research constructs across 320 respondents, each using a five-point scale. The mean values are fairly balanced, suggesting that participants generally expressed moderate perceptions of AI literacy, AI learning support, digital-financial readiness, AI-accounting technology anxiety, academic motivation, and

self-efficacy. Standard deviation values indicate sufficient response variability, allowing for reliable analysis. Slightly negative skewness and kurtosis values within acceptable limits suggest that the data distribution closely approximates normality, with no significant deviations. Overall, these descriptive results support the stability and suitability of the constructs for further measurement and evaluation of the structural model.

Table 2. Descriptive Statistics of Research Constructs

Construct	Code	N	Mean	SD	Min	Max	Skewness	Kurtosis
AI Literacy in Financial Education	AIL	320	3.141	0.9440	1.000	5.000	-0.05	-0.663
Perceived AI Learning Support	PALS	320	3.141	0.9490	1.000	5.000	-0.064	-0.715
Digital-Financial Learning Readiness	DFLR	320	3.141	0.9470	1.000	5.000	-0.113	-0.537

AI-Accounting Technology Anxiety	AAT A	32 0	3.14 1	0.95 00	1.0 00	5.0 00	-0.086	-0.713
Academic Motivation in AI-Enhanced Finance Learning	AMF	32 0	3.14 1	0.95 20	1.0 00	5.0 00	-0.195	-0.572
Student Self-Efficacy in AI-Driven Financial Management	SEA FM	32 0	3.14 1	0.93 90	1.0 00	5.0 00	-0.188	-0.740

Measurement Model Assessment

The measurement model assessment confirms that all constructs have acceptable reliability and validity. As detailed in Table 3, indicator outer loadings range from 0.807 to 0.876, exceeding the 0.70 threshold, thereby confirming indicator reliability. Internal consistency is strong, with Cronbach's alpha ranging from 0.894 to 0.904, rho_a from 0.894 to 0.909, and rho_c from 0.922 to 0.928, reflecting solid construct reliability. Convergent validity is demonstrated by AVE values ranging from 0.702 to 0.722, exceeding the 0.50 threshold. Additionally, Table 4 shows all HTMT values are below 0.85, with the highest between AMF and SEAFM, indicating adequate discriminant validity and that each construct is distinguishable. Overall, the measurement model

is robust and appropriate for further structural analysis.

Figure 2 presents the measurement model with standardized outer loadings for all reflective indicators. The results show that all indicators exceeded the recommended threshold of 0.70, with loadings ranging from 0.807 to 0.876, indicating satisfactory indicator reliability. Each construct also demonstrated adequate convergent validity, with AVE values ranging from 0.702 to 0.722 in the latent variable circles. Specifically, AATA recorded an AVE of 0.718, AIL of 0.710, AMF of 0.722, DFLR of 0.714, PALS of 0.717, and SEAFM of 0.702. These results confirm that the indicators consistently represent their respective constructs in the AI-driven financial management education model.

Table 3. Outer Loadings and Construct Reliability

Construct	Indicator	Outer Loading	Cronbach's Alpha	rho_a	rho_c	AVE
AI-Accounting Technology Anxiety	AATA1	0.861	0.902	0.909	0.927	0.718
	AATA2	0.856				
	AATA3	0.876				
	AATA4	0.807				
	AATA5	0.835				
AI Literacy in Financial Education	AIL1	0.833	0.898	0.898	0.924	0.710
	AIL2	0.847				
	AIL3	0.856				
	AIL4	0.836				
	AIL5	0.84				
Academic Motivation in AI-Enhanced Finance Learning	AMF1	0.865	0.904	0.905	0.928	0.722

Construct	Indicator	Outer Loading	Cronbach's Alpha	rho_a	rho_c	AVE
	AMF2	0.843				
	AMF3	0.829				
	AMF4	0.873				
	AMF5	0.837				
Digital-Financial Learning Readiness	DFLR1	0.834	0.9	0.902	0.926	0.714
	DFLR2	0.849				
	DFLR3	0.836				
	DFLR4	0.852				
	DFLR5	0.854				
Perceived AI Learning Support	PALS1	0.871	0.901	0.902	0.927	0.717
	PALS2	0.818				
	PALS3	0.844				
	PALS4	0.875				
	PALS5	0.824				
Student Self-Efficacy in AI-Driven Financial Management	SEAFM1	0.85	0.894	0.894	0.922	0.702
	SEAFM2	0.824				
	SEAFM3	0.831				
	SEAFM4	0.846				
	SEAFM5	0.838				

Table 4. HTMT

Construct	AATA	AIL	AMF	DFLR	PALS	SEAFM
AATA	—					
AIL	0.469	—				
AMF	0.460	0.573	—			
DFLR	0.388	0.530	0.587	—		
PALS	0.371	0.490	0.613	0.530	—	
SEAFM	0.553	0.636	0.705	0.593	0.640	—

Structural Model Assessment

The assessment of the structural model verified its statistical suitability for hypothesis testing. As detailed in Table 5, all inner VIF values ranged from 1.283 to 1.860, well below the threshold of 3.30, suggesting collinearity among the predictors is not an issue. The model's explanatory power is shown in Table 6, with Academic Motivation in AI-Enhanced Finance Learning reaching an R^2 of 0.462, and Student Self-Efficacy in AI-Driven Financial Management achieving an R^2 of 0.568. These figures indicate the model accounts for a moderate share of variance in both endogenous constructs. Furthermore, the Q^2 redundancy values for AMF (0.327) and SEAFM (0.391), along with the Q^2 predict values for AMF (0.446) and SEAFM (0.516), all of which are above zero, confirm the model's predictive relevance.

The results from Table 7 indicate that all the proposed structural paths were statistically significant. AI Literacy, Perceived AI Learning Support, and Digital-Financial Learning Readiness positively impacted both Academic Motivation and Student Self-Efficacy. Conversely, AI-Accounting Technology Anxiety had significant negative effects on these outcomes. Additionally, Academic Motivation positively influenced Student Self-Efficacy ($\beta = 0.268$, $p < 0.001$), highlighting its role as a key motivational factor in AI-based financial management education. Table 8's effect size analysis shows all f^2 values are small, with the strongest effect for PALS > AMF ($f^2 = 0.115$), followed by AMF > SEAFM ($f^2 = 0.089$), and PALS > SEAFM ($f^2 = 0.067$). Despite their small size, the significant paths, moderate R^2 , and positive predictive relevance collectively affirm the robustness of the structural model.

Table 5. Collinearity Assessment of Structural Predictors

Structural Path	VIF	Decision
AATA > AMF	1.283	Accepted
AATA > SEAFM	1.324	Accepted
AIL > AMF	1.509	Accepted
AIL > SEAFM	1.592	Accepted
AMF > SEAFM	1.86	Accepted
DFLR > AMF	1.496	Accepted
DFLR > SEAFM	1.599	Accepted
PALS > AMF	1.431	Accepted
PALS > SEAFM	1.596	Accepted

Table 6. Coefficient of Determination and Predictive Relevance

Endogenous Construct	R^2	Adjusted R^2	Q^2 Redundancy	Q^2 Predict
Academic Motivation in AI-Enhanced Finance Learning	0.462	0.455	0.327	0.446
Student Self-Efficacy in AI-Driven Financial Management	0.568	0.561	0.391	0.516

Table 7. Direct Effects of the Structural Model

Hypothesis	Structural Path	β	STDEV	t-value	p-value
H1	AIL > SEAFM	0.196	0.050	3.908	0.000
H2	PALS > SEAFM	0.214	0.047	4.549	0.000
H3	DFLR > SEAFM	0.129	0.047	2.747	0.006
H4	AATA > SEAFM	-0.188	0.039	4.789	0.000
H5	AIL > AMF	0.211	0.053	3.998	0.000
H6	PALS > AMF	0.298	0.049	6.077	0.000
H7	DFLR > AMF	0.236	0.052	4.565	0.000
H8	AATA > AMF	-0.148	0.045	3.274	0.001
H9	AMF > SEAFM	0.268	0.056	4.802	0.000

Table 8. Effect Size Assessment

Structural Path	f^2	Effect Size
AATA > AMF	0.032	Small
AATA > SEAFM	0.062	Small
AIL > AMF	0.055	Small
AIL > SEAFM	0.056	Small
AMF > SEAFM	0.089	Small
DFLR > AMF	0.069	Small
DFLR > SEAFM	0.024	Small
PALS > AMF	0.115	Small
PALS > SEAFM	0.067	Small

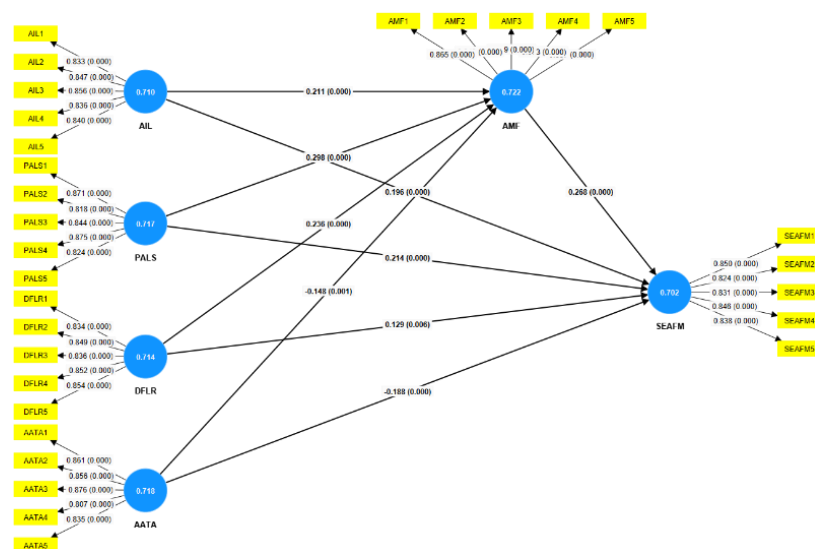


Figure 3. Structural Model

Figure 3 shows the bootstrapping results of the structural model. All direct paths are statistically significant, with PALS > AMF showing the strongest effect on Academic Motivation ($\beta = 0.298$, $p < 0.001$), followed by DFLR > AMF ($\beta = 0.236$, $p < 0.001$), AIL > AMF ($\beta = 0.211$, $p < 0.001$), and AATA > AMF with a negative effect ($\beta = -0.148$, $p = 0.001$). For Student Self-Efficacy, AMF > SEAFM has the strongest effect ($\beta = 0.268$, $p < 0.001$), followed by PALS > SEAFM ($\beta = 0.214$, $p < 0.001$), AIL > SEAFM ($\beta = 0.196$, $p < 0.001$), AATA > SEAFM negatively ($\beta = -0.188$, $p < 0.001$), and DFLR > SEAFM ($\beta = 0.129$, $p = 0.006$). These results indicate that AI-supported learning conditions significantly explain academic motivation and student self-efficacy in AI-driven financial management education.

Mediation Assessment

Table 9. Specific Indirect Effects of Academic Motivation

Hypothesis	Indirect Path	β	STDEV	t-value	p-value	95% CI
H10	AIL > AMF > SEAFM	0.056	0.019	2.998	0.003	0.023, 0.096
H11	PALS > AMF > SEAFM	0.080	0.021	3.730	<0.001	0.040, 0.124
H12	DFLR > AMF > SEAFM	0.063	0.020	3.159	0.002	0.029, 0.107
H13	AATA > AMF > SEAFM	-0.040	0.013	2.938	0.003	-0.068, -0.016

Discussion

The results indicate that student self-efficacy in AI-based financial management learning is influenced by a mix of technological, pedagogical, and discipline-specific factors. Instead of viewing AI simply as an accepted tool, the study reveals that students' confidence grows when they understand AI, receive effective learning support, can operate digital financial tools, manage technology-related anxiety, and remain academically motivated. This aligns with Social Cognitive Theory, which states that self-efficacy develops through mastery, vicarious learning, social persuasion, and emotional states (Bandura,

The mediation assessment examined the specific indirect effects of Academic Motivation in AI-Enhanced Finance Learning. As shown in Table 9, all indirect effects were statistically significant, as their confidence intervals did not include zero. Academic Motivation significantly mediated the relationships between AI Literacy and Student Self-Efficacy ($\beta = 0.056$, $p = 0.003$), Perceived AI Learning Support and Student Self-Efficacy ($\beta = 0.080$, $p < 0.001$), Digital-Financial Learning Readiness and Student Self-Efficacy ($\beta = 0.063$, $p = 0.002$), and AI-Accounting Technology Anxiety and Student Self-Efficacy ($\beta = -0.040$, $p = 0.003$). These findings indicate that students' motivation plays an important role in explaining how AI-related learning conditions translate into stronger or weaker self-efficacy in AI-driven financial management education.

1986). In accounting and financial management education, these sources of confidence are crucial because students must not only use AI tools but also assess financial explanations, verify outputs, and apply accounting principles responsibly. This supports previous research showing that AI competence and institutional AI capabilities can enhance students' self-efficacy, creativity, and learning outcomes (Murtono & Prayitno, 2025; Ryani Kusumawati, 2024; F. Wang et al., 2023; Y.-Y. Wang & Chuang, 2024).

AI literacy positively influences Financial Education by boosting students' confidence in using AI for their learning. Building on prior

research, this study examines accounting tasks where students assess the financial validity, conceptual accuracy, and ethical nature of AI explanations. Earlier research highlights the need for cognitive, behavioral, affective, and ethical skills to effectively interact with AI (Lintner, 2024; Ng et al., 2024). These findings reinforce the idea that AI literacy extends beyond digital familiarity, becoming a disciplinary skill in areas such as budgeting, forecasting, ratio analysis, and decision-making grounded in accounting principles. This echoes recent debates about tailoring AI literacy to specific fields rather than treating it as a general technical skill (Almatrafi et al., 2024; Chee et al., 2025).

Perceived AI Learning Support also plays a key role in boosting both academic motivation and self-efficacy. This indicates that students feel more confident when AI serves as a learning scaffold, offering explanations, feedback, alternative viewpoints, and guided practice. In financial management education, students often encounter complex and procedural topics such as capital budgeting, working capital analysis, financial forecasting, and risk-return assessment. AI support can help students break these down into smaller, more manageable learning steps. This aligns with research indicating that generative AI can enhance higher education by helping students clarify ideas, receive personalized guidance, and engage in self-regulated learning (Chan & Hu, 2023; Jin et al., 2023). Nonetheless, the educational value of AI hinges on students using it as a reflective learning partner rather than a shortcut for answers. This is especially important in accounting, where accuracy, judgment, and conceptual reasoning are vital to professional competence (Sundkvist & Kulset, 2024; Wood et al., 2023).

Digital Financial Learning Readiness also enhances academic motivation and students' self-efficacy. This suggests that students equipped to use digital platforms, spreadsheets, AI-supported applications, and finance-related tools are more likely to benefit from AI-enhanced learning. In accounting and financial management education, readiness goes beyond basic online learning skills; it includes the ability to combine AI outputs with

spreadsheet analysis, accounting systems, financial statement interpretation, and decision-support tools (Septiani et al., 2026). Previous research indicates that students' preparedness for online and AI-supported learning correlates with higher engagement, satisfaction, and performance in digital learning settings (Abuhassna et al., 2020; Van Wart et al., 2020; Wei & Chou, 2020). Our findings contribute a financial management angle, showing that readiness is even more valuable when students can apply AI-supported explanations to real analytical tasks. This supports the idea that AI-driven learning needs both conceptual understanding and practical fluency in finance-related skills (Delcker et al., 2024; Mah & Groß, 2024).

The negative impact of AI-Accounting Technology Anxiety is significant because it illustrates how emotional and ethical concerns can undermine students' confidence and motivation in AI-driven financial learning. Students might feel unsure when AI explanations conflict with lecturers' instructions, produce incorrect financial data, or raise integrity concerns. This is especially important in accounting education, which emphasizes accuracy, accountability, professional judgment, and ethics. Prior studies on generative AI in higher education have pointed out emotional tension, ethical uncertainty, assessment challenges, and concerns about responsible AI use (Qu et al., 2025; Xia et al., 2024). Similarly, research in accounting education warns that while AI can facilitate learning, students should be cautious about overreliance and verify AI-generated responses (Haugland Sundkvist & Kulset, 2024; Wood et al., 2023). Therefore, anxiety should not simply be seen as resistance to technology but as a sign that students need clearer teaching guidance, ethical limits, and validation methods.

The critical role of Academic Motivation indicates that students' confidence in AI-driven financial management learning is boosted when they see AI-supported education as valuable for skill development. Motivated learners are more inclined to test AI explanations, compare

financial options, verify outputs against accounting principles, and persist in solving complex problems. This aligns with Self-Determination Theory, which states that motivation increases when learning settings foster autonomy, competence, and meaningful engagement (Deci & Ryan, 1985; Ryan & Deci, 2000). The finding also supports expectancy-value theories in AI education, where students' willingness to learn with AI depends on perceived usefulness, supportive environments, and the importance they assign to AI-related learning (Chan & Zhou, 2023; Wang et al., 2023). Here, academic motivation is more than a general attitude; it serves as a mechanism that connects AI-supported learning conditions to students' confidence in performing accounting-focused financial tasks (Resti Wulansari & Daryono, 2025).

The mediation findings clarify how AI-related learning conditions impact student self-efficacy. AI literacy, perceived support for AI learning, and digital-financial readiness not only directly boost confidence but also enhance self-efficacy by motivating students to engage with AI-supported financial education. In contrast, anxiety about AI accounting technology diminishes self-efficacy, in part, by reducing students' motivation to use AI responsibly and critically. This pattern of mediation underscores that successful technology-based learning outcomes rely on both technological skills and motivational engagement (Lan & Hew, 2020; Mendoza et al., 2023). It aligns with experiential learning theory, which states that students build competence through interacting with real tasks, reflecting on results, validating interpretations, and applying knowledge to decision-making situations (Kolb, 1984). In AI-powered financial management education, academic motivation helps students transition from merely being exposed to tools to adopting disciplined learning practices.

These results contribute to the literature on accounting education and educational technology by providing a more domain-specific view of student self-efficacy in AI-assisted learning. While previous research has examined AI literacy,

perceptions of generative AI, online learning readiness, and AI self-efficacy in broader educational contexts (Crompton & Burke, 2023; Delcker et al., 2024; Y.-Y. Wang & Chuang, 2024), this study extends that research by applying these concepts to financial management and accounting education. Here, students must connect the use of AI to financial reasoning, calculation validation, ethical considerations, and professional skills (Avrila Pradita & Daryono, 2025). The results suggest that AI-powered financial education should do more than simply introduce AI tools. Educators should create learning activities that boost AI literacy, provide structured AI support, enhance digital-financial readiness, lessen anxiety, and stimulate academic motivation. This is especially relevant as generative AI becomes more integrated into accounting assessments, financial analysis, and career development (Abeysekera, 2024).

Conclusion

This research finds that student self-efficacy in AI-based financial management education is influenced by factors such as AI literacy, perceived AI learning support, digital-financial readiness, anxiety towards AI accounting technology, and academic motivation. Results show that students gain confidence when they understand AI capabilities, receive effective AI-enhanced learning support, and are prepared to use AI along with accounting and financial analysis tools. In contrast, anxiety about AI-accounting technology lowers their confidence and motivation. Furthermore, academic motivation serves as a key mediator, indicating that AI-related learning conditions affect self-efficacy both directly and through students' willingness to engage in AI-supported financial learning.

This study has some limitations. Firstly, data were gathered through a cross-sectional survey, so caution is needed when interpreting causality. Secondly, it relied on students' self-reported perceptions, which could be affected by response bias. Thirdly, the model focused on specific educational and technological factors but did not include others, such as lecturer competence,

curriculum design, AI ethics policy, and assessment methods. Future research could use longitudinal or experimental approaches, compare different accounting and finance courses, and explore how AI-based learning tools

impact students' financial reasoning, professional judgment, and academic integrity over time.

Appendix A. Research Instrument

Table A.1. Measurement Instrument for AI-Driven Financial Management Education

Variable	Code	Measurement Item	Scale	Source
AI Literacy in Financial Education	AIL1	I understand the basic functions and limitations of AI tools used in financial management learning.	Likert 1–5	Ng et al. (2024); Lintner (2024)
	AIL2	I can evaluate whether AI-generated financial explanations are conceptually accurate.	Likert 1–5	Ng et al. (2024); Koch et al. (2024)
	AIL3	I can use AI tools to support financial analysis without fully depending on them.	Likert 1–5	Chee et al. (2025); Almatrafi et al. (2024)
	AIL4	I consider ethical issues when using AI for accounting and financial management assignments.	Likert 1–5	Ng et al. (2024); Qu et al. (2025)
	AIL5	I can compare AI-generated answers with accounting and finance principles taught in class.	Likert 1–5	Sundkvist & Kulset (2024); Wood et al. (2023)
Perceived AI Learning Support	PALS1	AI tools help me understand difficult financial management concepts.	Likert 1–5	Chan & Hu (2023); Crompton & Burke (2024)
	PALS2	AI tools provide useful feedback when I solve finance-related problems.	Likert 1–5	Jin et al. (2023); Xia et al. (2024)
	PALS3	AI tools help me generate alternative explanations for accounting and finance topics.	Likert 1–5	Chan & Hu (2023); Sundkvist & Kulset (2024)
	PALS4	AI tools help me review financial calculations and decision-making steps.	Likert 1–5	Wood et al. (2023); Abeysekera (2024)
	PALS5	AI tools make financial management learning more personalized and accessible.	Likert 1–5	Chan & Hu (2023); Crompton & Burke (2023)
Digital-Financial Learning Readiness	DFLR1	I am ready to use digital tools for financial management learning activities.	Likert 1–5	Delcker et al. (2024); Van Wart et al. (2020)

Variable	Code	Measurement Item	Scale	Source
	DFLR2	I can combine AI tools with spreadsheets or financial software for coursework.	Likert 1–5	Wang et al. (2023); Joosten & Cusatis (2020)
	DFLR3	I can independently learn new digital applications related to accounting and finance.	Likert 1–5	Van Wart et al. (2020); Abuhassna et al. (2020)
	DFLR4	I have sufficient digital skills to complete AI-assisted finance assignments.	Likert 1–5	Delcker et al. (2024); Mah & Groß (2024)
	DFLR5	I can adapt quickly when lecturers introduce new AI-based learning tools.	Likert 1–5	Crompton & Burke (2024); Wang & Chuang (2024)
AI-Accounting Technology Anxiety	AATA1	I feel anxious when AI produces financial answers that I cannot verify.	Likert 1–5	Lund et al. (2024); Chan & Hu (2023)
	AATA2	I worry that using AI in accounting assignments may lead to academic misconduct.	Likert 1–5	Qu et al. (2025); Xia et al. (2024)
	AATA3	I feel uncertain when AI explanations differ from my lecturer's explanation.	Likert 1–5	Sundkvist & Kulset (2024); Wood et al. (2023)
	AATA4	I am concerned that AI tools may weaken my own financial reasoning skills.	Likert 1–5	Chan & Hu (2023); O'Dea (2024)
	AATA5	I feel nervous when I have to use AI-based accounting or finance software.	Likert 1–5	Lund et al. (2024); Zhao & Wang (2024)
Academic Motivation in AI-Enhanced Finance Learning	AMF1	I am motivated to use AI to deepen my understanding of financial management.	Likert 1–5	Wang et al. (2023); Chan & Zhou (2023)
	AMF2	I use AI because it helps me become more competent in accounting-related finance tasks.	Likert 1–5	Mendoza et al. (2023); Wang & Chuang (2024)
	AMF3	I feel encouraged to explore financial management cases with AI assistance.	Likert 1–5	Chan & Zhou (2023); Jin et al. (2023)
	AMF4	I believe AI-supported learning is valuable for my future career in accounting or finance.	Likert 1–5	Wang et al. (2023); Southworth et al. (2023)

Variable	Code	Measurement Item	Scale	Source
	AMF5	I am willing to invest effort in learning how to use AI responsibly for finance learning.	Likert 1–5	Ng et al. (2024); Chee et al. (2025)
Student Self-Efficacy in AI-Driven Financial Management	SEAFM1	I am confident that I can use AI to support financial management problem-solving.	Likert 1–5	Wang & Chuang (2024); Wang et al. (2023)
	SEAFM2	I can critically evaluate AI-generated financial recommendations.	Likert 1–5	Wang & Chuang (2024); Ng et al. (2024)
	SEAFM3	I can use AI to improve my understanding of budgeting, forecasting, and financial analysis.	Likert 1–5	Abeysekera (2024); Zhao & Wang (2024)
	SEAFM4	I can complete AI-assisted finance assignments while maintaining academic integrity.	Likert 1–5	Qu et al. (2025); Xia et al. (2024)
	SEAFM5	I am confident that AI-supported learning improves my readiness for practice in accounting and finance.	Likert 1–5	Wang et al. (2023); Sundkvist & Kulset (2024)

References

- Abeysekera, I. (2024). ChatGPT and academia on accounting assessments. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(1). <https://doi.org/10.1016/j.joitmc.2024.100213>
- Abuhassna, H., Al-Rahmi, W. M., Yahya, N., Zakaria, M. A. Z. M., Kosnin, A. B. M., & Darwish, M. (2020). Development of a new model on utilizing online learning platforms to improve students' academic achievements and satisfaction. *International Journal of Educational Technology in Higher Education*, 17(1). <https://doi.org/10.1186/s41239-020-00216-z>
- Almatrafi, O., Johri, A., & Lee, H. (2024). A systematic review of AI literacy conceptualization, constructs, and implementation and assessment efforts (2019–2023). *Computers and Education Open*, 6. <https://doi.org/10.1016/j.caeo.2024.100173>
- Arifah, S., & Rizki Nugraha, A. (2024). The Short Term Earnings Management Ethic and Its Effect on Accounting Education and Corporate Perceptions. *Advances in Accounting Innovation*, 1(1 SE-Article).
- Avrila Pradita, N., & Daryono. (2025). Islamic FinTech Adoption Sharia Compliance Gender Trust. *Journal International Economic Sharia*, 2(2). <https://doi.org/10.69725/jies.v2i2.291>
- Bandura, A. (1986). *Social foundations of thought and action: a social cognitive theory* / Albert Bandura. New Jersey: Prentice-Hall, 1986, 16(1).
- Bandura, A., Freeman, W. H., & Lightsey, R. (1999). Self-Efficacy: The Exercise of Control. *Journal of Cognitive Psychotherapy*, 13(2). <https://doi.org/10.1891/0889-8391.13.2.158>
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20(1). <https://doi.org/10.1186/s41239-023-00411-8>
- Chan, C. K. Y., & Zhou, W. (2023). An expectancy value theory (EVT) based instrument for measuring student perceptions of generative AI. *Smart Learning Environments*, 10(1). <https://doi.org/10.1186/s40561-023-00284-4>

- Chee, H., Ahn, S., & Lee, J. (2025). A Competency Framework for AI Literacy: Variations by Different Learner Groups and an Implied Learning Pathway. In *British Journal of Educational Technology* (Vol. 56, Number 5). <https://doi.org/10.1111/bjet.13556>
- Cheng, C. C., Wang, J. S., Zhai, X., & Yang, Y. T. C. (2025). AI literacy and gender equity in elementary education: A quasi-experimental study of a STEAM-PBL-AIoT course with questionnaire validation. *International Journal of STEM Education*, 12(1). <https://doi.org/10.1186/s40594-025-00574-y>
- Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, 20(1). <https://doi.org/10.1186/s41239-023-00392-8>
- Darsono, T., Haryono, T., Setiawan, A. I., Harsono, M., Wijayanto, H., & Dwianto, A. (2026). Managing Assistive Technology Adoption for Sustainable Special Education Performance. *International Journal of Special Education*, 41(2S), 409–426. <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105041508148&partnerID=40&md5=1d81b9d46332d25a4c4d3e2764215643>
- Deci, E. L., & Ryan, R. M. (1985). Intrinsic Motivation and Self-Determination in Human Behavior. In *Intrinsic Motivation and Self-Determination in Human Behavior*. <https://doi.org/10.1007/978-1-4899-2271-7>
- Delcker, J., Heil, J., Ifenthaler, D., Seufert, S., & Spirgi, L. (2024). First-year students AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education*, 21(1). <https://doi.org/10.1186/s41239-024-00452-7>
- Dwianto, A., Qurrota A'yun, A., & Sabila, I. (2025). Mobile AI Applications to Support QRIS Literacy and Financial Growth of Traditional Market SMEs. *Journal Economic Business Innovation*, 2(1). <https://doi.org/10.69725/jebi.v2i1.234>
- Edwards, J., Nguyen, A., Lämsä, J., Sobocinski, M., Whitehead, R., Dang, B., Roberts, A. S., & Järvelä, S. (2025). Human-AI collaboration: Designing artificial agents to facilitate socially shared regulation among learners. *British Journal of Educational Technology*, 56(2). <https://doi.org/10.1111/bjet.13534>
- Gašević, D., Siemens, G., & Sadiq, S. (2023). Empowering learners for the age of artificial intelligence. In *Computers and Education: Artificial Intelligence* (Vol. 4). <https://doi.org/10.1016/j.caeai.2023.100130>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate aata analysis* (8th ed.). Cengage Learning. In *Gedrag & Organisatie* (Vol. 19, Number 3).
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Number 1). <https://doi.org/10.1108/EBR-11-2018-0203>
- Haugland Sundkvist, C., & Kulset, E. M. (2024). Teaching accounting in the era of ChatGPT – The student perspective. *Journal of Accounting Education*, 69. <https://doi.org/10.1016/j.jaccedu.2024.100932>
- Jin, S. H., Im, K., Yoo, M., Roll, I., & Seo, K. (2023). Supporting students' self-regulated learning in online learning using artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, 20(1). <https://doi.org/10.1186/s41239-023-00406-5>
- Joosten, T., & Cusatis, R. (2020). Online Learning Readiness. *American Journal of Distance Education*, 34(3). <https://doi.org/10.1080/08923647.2020.1726167>
- Kolb, D. A. (1984). *Experiential Learning: Experience as The Source of Learning and Development*. Prentice Hall, Inc., (1984). <https://doi.org/10.1016/B978-0-7506-7223-8.50017-4>
- Lan, M., & Hew, K. F. (2020). Examining learning engagement in MOOCs: a self-determination theoretical perspective using mixed method. *International Journal of Educational Technology in Higher Education*, 17(1). <https://doi.org/10.1186/s41239-020-0179-5>
- Lintner, T. (2024). A systematic review of AI literacy scales. *Npj Science of Learning*, 9(1). <https://doi.org/10.1038/s41539-024-00264-4>
- Lund, B. D., Mannuru, N. R., & Agbaji, D. (2024). AI anxiety and fear: A look at perspectives of information science students and professionals towards artificial intelligence. *Journal of Information Science*. <https://doi.org/10.1177/01655515241282001>

- Lund, B. D., & Naheem, K. T. (2024). Can ChatGPT be an author? A study of artificial intelligence authorship policies in top academic journals. *Learned Publishing*, 37(1). <https://doi.org/10.1002/leap.1582>
- Mah, D. K., & Groß, N. (2024). Artificial intelligence in higher education: exploring faculty use, self-efficacy, distinct profiles, and professional development needs. *International Journal of Educational Technology in Higher Education*, 21(1). <https://doi.org/10.1186/s41239-024-00490-1>
- Mendoza, N. B., Yan, Z., & King, R. B. (2023). Supporting students' intrinsic motivation for online learning tasks: The effect of need-supportive task instructions on motivation, self-assessment, and task performance. *Computers and Education*, 193. <https://doi.org/10.1016/j.compedu.2022.104663>
- Murtono, & Prayitno, M. (2025). Postgraduate Learning Innovation in the Age of Artificial Intelligence. *Advances Educational Innovation*, 1(3 SE-Articles).
- Ng, D. T. K., Wu, W., Leung, J. K. L., Chiu, T. K. F., & Chu, S. K. W. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology*, 55(3). <https://doi.org/10.1111/bjet.13411>
- Ning, Y., Zhang, W., Yao, D., Fang, B., Xu, B., & Wijaya, T. T. (2025). Development and validation of the Artificial Intelligence Literacy Scale for Teachers (AILST). *Education and Information Technologies*, 30(12). <https://doi.org/10.1007/s10639-025-13347-5>
- O'Dea, X. (2024). Generative AI: is it a paradigm shift for higher education? *Studies in Higher Education*, 49(5). <https://doi.org/10.1080/03075079.2024.2332944>
- Qu, Y., Loo, H. E., & Wang, J. (2025). Generative artificial intelligence in higher education: Emotional tensions and ethical declaration. *British Journal of Educational Technology*. <https://doi.org/10.1111/bjet.70029>
- Resti Wulansari, A., & Daryono. (2025). Islamic Microfinance, Self-Efficacy, and Women's Economic Resilience. *Journal International Economic Sharia*, 2(2). <https://doi.org/10.69725/jies.v2i2.290>
- Ryan, R. M., & Deci, E. L. (2000). Self-Determination Theory. *Encyclopedia of Quality of Life and Well-Being Research*. In American Psychologist.
- Ryani Kusumawati, R. (2024). Leveraging Artificial Neural Networks to Predict and Enhance Student Performance in Virtual Learning Environments. *Researcher Academy Innovation Data Analysis*, 1(2). <https://doi.org/10.69725/raida.v1i2.162>
- Septiani, I. T., Haryanti, S. S., & Khristiana, Y. (2026). Determinants of Fintech Usage among University Students: The Roles of Personal Financial Management, Consumptive Behavior, and Investment Interest. *Journal Economic Business Innovation*, 3(1), 41–52. <https://doi.org/10.69725/jebi.v3i1.351>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, 53(11). <https://doi.org/10.1108/EJM-02-2019-0189>
- Van Wart, M., Ni, A., Medina, P., Canelon, J., Kordrostami, M., Zhang, J., & Liu, Y. (2020). Integrating students' perspectives about online learning: a hierarchy of factors. *International Journal of Educational Technology in Higher Education*, 17(1). <https://doi.org/10.1186/s41239-020-00229-8>
- Wang, F., King, R. B., Chai, C. S., & Zhou, Y. (2023). University students' intentions to learn artificial intelligence: the roles of supportive environments and expectancy–value beliefs. *International Journal of Educational Technology in Higher Education*, 20(1). <https://doi.org/10.1186/s41239-023-00417-2>
- Wang, Y.-Y., & Chuang, Y.-W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, 29(4), 4785–4808. <https://doi.org/10.1007/s10639-023-12015-w>
- Wei, H. C., & Chou, C. (2020). Online learning performance and satisfaction: do perceptions and readiness matter? *Distance Education*, 41(1). <https://doi.org/10.1080/01587919.2020.1724768>
- Wood, D. A., Achhpilia, M. P., Adams, M. T., Aghazadeh, S., Akinyele, K., Akpan, M., Allee, K. D., Allen, A. M., Almer, E. D., Ames, D., Arity, V., Barr-Pulliam, D., Basoglu, K. A., Belnap, A., Bentley, J. W., Berg, T., Berglund, N. R., Berry, E., Bhandari, A., ... Zoet, E. (2023). The ChatGPT Artificial Intelligence Chatbot: How Well Does It Answer Accounting Assessment Questions? *Issues in Accounting Education*, 38(4). <https://doi.org/10.2308/ISSUES-2023-013>

Xia, Q., Weng, X., Ouyang, F., Lin, T. J., & Chiu, T. K. F. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. In *International Journal of Educational Technology in Higher Education* (Vol. 21, Number 1). <https://doi.org/10.1186/s41239-024-00468-z>

Acknowledgments

The authors would like to express their sincere appreciation to the Faculty of Economics and Business, Universitas Diponegoro, for academic support during the preparation of this study. The authors also thank the students who participated in the survey and provided valuable responses for this research. Appreciation is further extended to colleagues and academic reviewers who offered constructive feedback that helped improve the manuscript's quality. No external funding was received for this study.

Author Declaration

The authors confirm that this manuscript is original, has not been published previously, and is not currently under consideration for publication elsewhere. All authors have made substantial contributions to the conception, design, analysis, interpretation, and preparation of the manuscript, and all authors have read and approved the final version for submission.

The authors declare no conflicts of interest related to this study. No financial, institutional, or personal relationships influenced the research design, data analysis, interpretation of findings, or manuscript preparation.