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Mediating Role of Artificial Intelligence in Linking Self-Efficacy and Learner Performance

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Abstract
The integration of Artificial Intelligence (AI) into education continues to expand, yet its effectiveness in improving learning outcomes requires further examination, particularly with regard to the role of self-efficacy in digital learning in Indonesia. This study extends Bandura's self-efficacy construct by conceptualizing AI as a latent mediating variable functioning as an adaptive educational mechanism through feedback, personalized resources, and dynamic scaffolding. A quantitative approach was employed via an online survey conducted between February and May 2024, yielding 279 valid responses from secondary and higher education students across several Indonesian provinces. Data were analyzed using SEM-PLS with SmartPLS 3.0. The results show that self-efficacy moderately predicts AI adoption (β = 0.373 = 0.373), AI integration strongly predicts learning behavior and performance (β = 0.373 = 0.649), while the direct pathway from self-efficacy is relatively weak (β = 0.373 = 0.144), with the indirect pathway mediated by AI substantially stronger (mediation effect = 0.242). Theoretically, these findings enrich Bandura's framework of self-efficacy in the context of digital learning by highlighting AI as a central mediating construct, while practically they provide implications for adaptive learning strategies, digital education policy, and technology-driven pedagogical innovation.

Keywords: Artificial Intelligence, Self-Efficacy, Learning Behavior Performance, Mediating Role

1. Introduction

Artificial intelligence (AI) has progressed rapidly over the past decade, with education emerging as one of the most profoundly affected domains. Beyond its broader applications in healthcare [1], industry [2], and government [3], AI has become a transformative force in technology-enhanced learning. It is increasingly integrated into educational contexts to support instruction, assessment, and learner engagement, thereby reshaping how students acquire knowledge and develop competencies [4, 5].

Within the educational context, AI-driven tools such as adaptive learning systems, academic chatbots, and recommendation algorithms are widely utilized to enhance instructional effectiveness and personalize learning experiences [6, 7, 8, 9]. While existing studies have underscored AI's potential to broaden access and improve institutional efficiency, its impact on students' psychological dimensions—particularly self-efficacy (SE)—remains a subject of scholarly debate. Self-efficacy, defined as an individual's belief in their ability to execute specific tasks [10] is a critical determinant of motivation, persistence, and academic achievement [11]. Consequently, understanding how AI influences learners' self-efficacy is essential for designing pedagogical interventions that not only optimize learning outcomes but also strengthen students' psychological readiness to thrive in AI-mediated learning environments.

Prior research has established a substantial association between digital technologies and academic self-efficacy. Lee et al. [12] examined the relationship between AI self-efficacy and academic dishonesty, finding that students' perceptions of AI substantially influenced their ethical judgments and psychological decision-making within learning contexts. Similarly, Imran et al. [13] investigated the relationship between AI self-efficacy and academic dishonesty, finding that students' perceptions of AI significantly influenced their ethical judgments and psychological decision-making within learning contexts. A systematic review by Samala et al. [14] further underscored that while AI tools such as ChatGPT can expand access to information, they may also present challenges to creativity and critical thinking.

Beyond self-efficacy, learning performance constitutes a critical variable in evaluating AI-mediated education. It is commonly assessed through indicators such as student engagement, academic achievement, and task productivity. Liao et al. [15] demonstrated that AI-based learning systems can improve academic outcomes when combined with reflective learning strategies and constructive feedback mechanisms. Although the adoption of AI in Indonesia's education sector remains in its nascent stage, it exhibits considerable potential to enhance instructional effectiveness, streamline administrative processes, and foster student engagement. Government initiatives such as the Merdeka Belajar program and the expansion of online learning platforms have accelerated the digital transformation of the national education landscape [16]. These developments create opportunities for the implementation of AI-based technologies, including intelligent tutoring systems, automated assessment, predictive analytics, and adaptive learning environments tailored to individual learning styles.

A notable research gap persists concerning the intersection of AI and psychological constructs — particularly self-efficacy—within the Indonesian educational context. While global scholarship on AI in education has expanded substantially, empirical research in Indonesia remains limited and has predominantly focused on technical [17, 18] or administrative aspects of digital adoption [19, 20]. Few investigations have explicitly examined how AI-based technologies influence students' confidence in their ability to succeed academically. This omission is critical, as self-efficacy is consistently recognized as a strong predictor of motivation, persistence, and academic achievement [10, 21]. At the same time, AI holds the potential to promote personalized learning [22], foster learner autonomy [23], and reshape psychological engagement [23] in learning environments. Addressing this gap is therefore essential for advancing both theoretical understanding and practical applications of AI in education, particularly in developing-country contexts such as Indonesia.

Addressing both conceptual and empirical gaps in the existing literature, this study adopts Bandura's self-efficacy framework [10] and extends it by incorporating artificial intelligence (AI) as a novel exogenous construct within the proposed conceptual model (see Figure 1). The investigation examines the mediating role of AI in the relationship between self-efficacy, learning behavior, and academic performance. By analysing the dynamic interplay between psychological constructs and AI-mediated learning experiences, this study aims to elucidate how AI can enhance students' academic confidence and foster improved learning outcomes across diverse educational contexts.

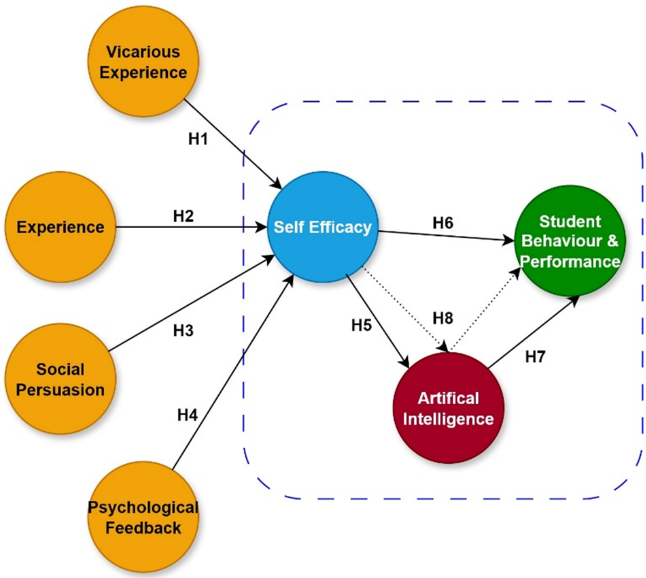


Figure 1. Conceptual Framework.

The development of the research hypotheses follows a systematically structured conceptual framework. It commences with an exposition of the four principal sources of self-efficacy—vicarious experience (VE), mastery experience (EX), social persuasion (SP), and physiological feedback (PF)—and subsequently advances to the core construct of self-efficacy, student learning behavior and performance (SBP), the integration of artificial intelligence (AI), and finally, the mediating role of AI in the relationship between self-efficacy and performance. Each component is delineated in detail to substantiate the formulation of empirically testable hypotheses within the proposed research model.

Vicarious experience pertains to the formation of efficacy beliefs through the observation of others' successes, including those of peers, seniors, or role models. Within Indonesia's collectivist cultural context, social learning through observation assumes a particularly prominent role, especially in educational settings that prioritize communal values, exemplary behavior, and interpersonal harmony [24]. When students observe the academic achievements of individuals they perceive as similar or relatable, they are more likely to internalize these experiences as positive benchmarks for their own capabilities. This observational process not only enhances perceived self-competence but also cultivates motivation and strengthens expectations of success in confronting academic challenges.

H1: Vicarious experience positively affects self-efficacy.

Direct experience is widely regarded as the most influential source of self-efficacy, as it entails personal mastery achieved through the successful completion of tasks. Within the Indonesian education system, which places a strong emphasis on achievement outcomes and examination-based assessments, independent success in academic activities serves as a critical determinant of perceived competence. When students are able to surmount academic challenges autonomously, they internalize these accomplishments as concrete evidence of their abilities, thereby strengthening their academic self-efficacy. Such mastery experiences not only affirm one's perceived capability but also foster intrinsic motivation and perseverance in the learning process.

H2: Direct experience positively affects self-efficacy.

Social persuasion encompasses verbal encouragement, motivational support, and reinforcement from external agents such as teachers, lecturers, parents, and other authority figures. Within the Indonesian educational context, which upholds respect for authority and familial values, social persuasion significantly shapes students' beliefs about their academic competence. Affirmative feedback, recognition, and motivational discourse from respected figures serve not only as emotional reinforcement but also as social validation of one's ability. Pedagogical interactions infused with social persuasion can enhance intrinsic motivation and strengthen self-efficacy, particularly in high-pressure academic situations.

H3: Social persuasion positively affects self-efficacy.

Psychological feedback pertains to the emotional and physiological states experienced during academic activities. This source of efficacy is influenced by internal responses to learning situations, such as anxiety, stress, or psychological comfort. In Indonesia, systemic academic pressures—such as national examinations, university entrance selection, and performance-based assessments—often trigger emotional tension that may undermine academic confidence. However, students who can regulate stress and maintain emotional stability during learning tend to exhibit higher levels of academic self-efficacy. Positive psychological states facilitate concentration and perseverance and reinforce perceptions of competence.

H4: Psychological feedback positively affects self-efficacy.

Self-efficacy has been demonstrated to influence not only students' engagement in learning activities but also their willingness to adopt and effectively use emerging technologies. Learners with a high sense of self-efficacy are more inclined to explore, adapt to, and proficiently utilize AI-powered tools for academic purposes, thereby enhancing their learning behaviors and overall performance outcomes.

H5: Self-efficacy positively influences the utilization of AI in learning.

H6: Self-efficacy positively influences students' learning behavior and performance.

AI technologies can provide personalized learning experiences, adaptive feedback, and tailored resources that support student engagement and academic success. As such, AI use in learning environments is expected to have a direct positive impact on both learning behavior and performance.

H7: AI positively influences students' learning behavior and performance.

In addition to its direct effects, AI mediates the relationship between self-efficacy and learning outcomes by transforming confidence into measurable gains. This occurs through personalized feedback that refines learning strategies [25], adaptive scaffolding that aligns tasks and resources with individual needs [26], and real-time support that sustains engagement and persistence [27]. Together, these mechanisms demonstrate how AI enables self-efficacy to translate more effectively into students' behavior and performance.

H8: AI mediates the relationship between self-efficacy and students' learning behavior and performance.

Considering the geographic diversity, institutional heterogeneity, and disparities in technological accessibility across regions of Indonesia, the findings of this study are anticipated to provide both theoretical and practical contributions to the fields of educational psychology and technology-enhanced learning. Theoretically, the study aims to advance scholarly discourse by integrating psychological constructs with AI-mediated learning frameworks within the context of a developing nation. Practically, the empirical insights derived from this research are expected to offer an evidence-based foundation for the development of AI-driven educational policies that are contextually adaptive, socially inclusive, and strategically aligned with efforts to strengthen student competencies in the era of digital transformation.

2. Methods

2.1 Data Collection

Quantitative data were obtained through an online questionnaire administered via Google Forms (https://docs.google.com/forms) to students at the secondary, undergraduate, masters, and doctoral levels across several provinces in Indonesia. Participants were selected using purposive sampling, with inclusion criteria based on their engagement in AI-related activities within their respective fields of study to ensure alignment with the research objectives. Data collection was carried out between February and May 2024, resulting in 287 valid responses that met the preliminary inclusion criteria. Informed consent was secured from all participants, and anonymity was maintained throughout the research process.

The questionnaire was designed to measure several theoretical constructs, including vicarious experience, direct experience, social persuasion, psychological feedback, self-efficacy, artificial intelligence, and student behaviour and performance. A rigorous data screening procedure was subsequently conducted to eliminate incomplete or analytically invalid responses, resulting in a final dataset of 279 valid cases for analysis. The demographic characteristics of the respondents are presented in Table 1.

Table 1. Respondents Profile

Measuring	Items	n	%
Gender distribution	Male	173	62.01
	Female	106	37.99
Age	Under 20 years	89	31.90
	21-25 years	61	21.86
	26-40 years	76	27.24
	41-50 years	50	17.92
	Over 50 years	3	1.08
Duration of AI Use	Never	13	4.66
	1 years	177	63.44
	2 years	69	24.73
	3 years	7	2.51
	>3 years	13	4.66
AI Platform Preferences	Web	228	81.72
	Mobile Apps	16	5.73
	Web & Mobile Apps	35	12.54
License categories	Free	275	98.57
	Paid	4	1.43
Educational Background	Senior High School	9	3.23
	Bachelor's	223	79.93
	Master's	25	8.96
	Doctoral	22	7.89

2.2 Measurement

Following consultations with three domain experts specializing in education, artificial intelligence, and the social sciences, this study initially developed 37 questionnaire items to represent the theoretical constructs under investigation for hypothesis testing. A preliminary elimination process and pilot testing involving 40 respondents were subsequently conducted to assess item clarity, conceptual relevance, and internal consistency. Based on the results of these assessments, 28 items were retained for inclusion in the main data collection phase.

Drawing on Usher and Pajares [28], three items representing the vicarious experience construct were adapted from the original six-item scale (e.g., "Seeing adults do well in math pushes me to do better," "When I see how my math teacher solves a problem, I can picture myself solving the problem in the same way"). Thematic analysis identified three salient conceptual dimensions—see, feel, and learn—which served as the theoretical foundation for constructing three refined items. These revised items provide a more concise and conceptually coherent representation of the vicarious experience construct.

From the same source, six items measuring the direct experience construct were examined. A thematic analysis yielded four refined items reflecting the conceptual keywords extensive, success, experience, and learn (e.g., "I have successfully tackled difficult academic challenges in the past," "My previous experiences help me feel confident in facing new challenges"). These items were selected for their semantic clarity and theoretical alignment with self-efficacy, ensuring that the scale captures the depth and relevance of prior academic experiences as a critical source of efficacy beliefs.

Likewise, the original social persuasion construct consisted of six items (e.g., "My math teachers have told me that I am good at learning math," "Adults in my family have told me what a good math student I am"). A thematic analysis identified three primary sources of motivation: lecturers, peers, and others. Based on these dimensions, three refined items were developed: "Support from lecturers increases my confidence in learning," "My peers motivate me to complete academic tasks," and "Praise from others encourages me to try new things."

The psychological feedback construct was adapted from the psychological state construct, while retaining the same conceptual meaning. The original scale consisted of six items, which were refined into three items without altering their substantive content. For example, the original item "Just being in math class makes me feel stressed and nervous" was transformed as "I feel stressed when confronted with difficult academic tasks." Whereas the original scale predominantly emphasized negative psychological states such as stress and pressure, the refined version introduced a more balanced perspective by incorporating normal or positive states, for instance, "I remain calm when facing academic challenges."

In developing the self-efficacy construct, we began by examining nine items from Yamada et al. [29], originally derived from Pintrich and De Groot [30]. While these items provided a solid foundation, further refinement was needed to align them with the study's context. To achieve this, we drew on Bandura's Children's Self-Efficacy Scale, which highlights key domains of academic achievement, self-regulated learning, and extracurricular engagement. One notable adjustment was the simplification of the response format: the original 0–100 confidence scale (Cannot do at all to Highly certain can do) was transformed into a more practical Likert scale. In this process, items such as "Finish my homework assignments by deadlines" and "Plan my schoolwork for the day" were reformulated into broader, more integrative statements like "I can manage my time and complete tasks efficiently" and "I feel in control of my learning process." Through this refinement, the construct was streamlined into five items that retained the essence of the original measures while enhancing clarity and applicability.

A total of five items were employed to measure the construct of student behavior and performance, consisting of three items representing behavior ("I actively engage in independent learning activities," "I take initiative to explore learning materials beyond the curriculum," "I am highly motivated to learn") and two items representing performance ("I achieve satisfactory academic outcomes," "I follow my study schedule with discipline"). The construct was adapted from Nurtanto et al. [31]. The student behavior items were reduced from four to three, while the performance items were refined from five to two to ensure better alignment with the study's context.

The final construct is AI. Its development was grounded in the Unified Theory of Acceptance and

Use of Technology (UTAUT) proposed by Venkatesh et al. [32], with particular emphasis on the dimension of performance expectancy. Performance expectancy refers to the extent to which an individual believes that using a system will improve job performance. Five items were developed and validated in accordance with the performance expectancy indicators outlined by Nurtanto et al. [31]. Sample items include: "AI tools help me understand academic material more effectively" and "I frequently use AI as a learning aid."

Data analysis was performed using SMART-PLS version 3.0, which facilitates the simultaneous assessment of both the measurement and structural models within the Partial Least Squares Structural Equation Modeling (PLS-SEM) framework. The initial phase involved evaluating construct validity through the outer model, encompassing analyses of convergent validity, discriminant validity, and composite reliability. Subsequently, the inner model was assessed by examining the R^2 values, path coefficients, and effect sizes to determine the strength and significance of both direct and indirect relationships among the hypothesized variables.

3. Results and Discussion

3.1 Results

Demographic Profile As shown in Table 1, the study included 279 respondents, predominantly male (62.01%) and from younger age groups, particularly those under 20 years (31.90%) and 26–40 years (27.24%). Most respondents reported one year of experience with AI tools (63.44%), accessed them primarily via web-based platforms (81.72%), and relied on free services (98.57%). The majority also held undergraduate qualifications (79.93%), reflecting the strong engagement of digitally literate youth in utilizing accessible web-based AI technologies.

Validity and Reliability, The measurement model demonstrated adequate reliability and validity (Tables 2-3 and Figure 3). All constructs satisfied the recommended thresholds for Cronbach's Alpha (≥ 0.70), composite reliability (CR ≥ 0.70), and average variance extracted (AVE ≥ 0.50), confirming internal consistency and convergent validity [33].

The heterotrait-monotrait ratio of correlations (HTMT) was employed to evaluate discriminant validity among the latent constructs. As presented in Table 4 and Figure 2, all HTMT values fall below the conservative threshold of 0.85 [34] and remain well under the more liberal cut-off of 0.90 suggested by Henseler et al. [35]. These results confirm that each construct exhibits satisfactory discriminant validity. Specifically, the highest HTMT value was observed between SE and VE at 0.794, followed closely by SE and PF at 0.785. Both values remain within acceptable limits, suggesting that although the constructs are conceptually related, they are empirically distinct. Similarly, SP and VE yielded an HTMT of 0.806, which also satisfies the threshold criteria.

The relatively low correlations, such as between AI and EX (0.316), further reinforce the discriminant validity of the measurement model. Overall, these results confirm that multicollinearity is not a concern and that the constructs capture unique dimensions of the conceptual framework.

Table 2. The Inner Model Quality

Instrument	Loadings	CR	α	AVE	Ref
Vicarious Experience (VI)					
I feel more confident after observing others successfully complete similar tasks.	0.741	0.837	0.708	0.632	[28]
Seeing my peers succeed makes me believe I can succeed too.	0.828				
I learn how to handle challenges by observing others' experiences.	0.813				

Experience (EX)					
I have extensive experience completing academic tasks independently.	0.833	0.916	0.878	0.731	[28]
I have successfully tackled difficult academic challenges in the past.	0.857				
My previous experiences help me feel confident in facing new challenges.	0.878				
I learn from my own experiences to improve performance.	0.851				
Social Persuasion (SP)					
Support from lecturers increases my confidence in learning.	0.849	0.911	0.854	0.773	[28]
My peers motivate me to complete academic tasks.	0.903				
Praise from others encourages me to try new things.	0.886				
Psychological Feedback (PF)					
I remain calm when facing academic challenges.	0.858	0.914	0.859	0.780	[28]
I feel stressed when confronted with difficult academic tasks.	0.920				
My emotional state affects my confidence level.	0.871				
Self-Efficacy (SE)					
I believe I am capable of performing well in academic tasks.	0.739	0.867	0.808	0.566	[29]
I am confident in overcoming learning obstacles.	0.807				
I can manage my time and complete tasks efficiently.	0.715				
I feel in control of my learning process.	0.757				
I am confident when facing academic evaluations.	0.742				
Artificial Intelligence (AI)					
AI tools help me understand academic material more effectively.	0.879	0.938	0.918	0.752	[31, 32]
I feel comfortable using AI in my learning activities.	0.879				
AI helps me complete academic tasks efficiently.	0.886				
I believe AI can enhance my academic performance.	0.859				
I frequently use AI as a learning aid.	0.834				
Student Behavior	Performance (SBP)				
I actively engage in independent learning activities.	0.833	0.920	0.891	0.697	[31]
I take initiative to explore learning materials beyond the curriculum.	0.787				
I am highly motivated to learn.	0.819				
I achieve satisfactory academic outcomes.	0.870				
I follow my study schedule with discipline.	0.864				

Table 3. Fornell-Lacker Criterion Result

Construct SBP	AI VE	EX	PF	SE	SP
AI	0.867				
EX	0.286	0.855			

PF	0.343	0.569	0.883				
SE	0.373	0.558	0.660	0.753			
SP	0.368	0.483	0.496	0.618	0.879		
SBP	0.702	0.382	0.356	0.386	0.359	0.835	
VE	0.394	0.514	0.519	0.607	0.633	0.392	0.795

Table 4. Heterotrait Monotrait Ratio (HTMT)

Construct	AI	EX	PF	SE	SP	SBP	VE
AI							
EX	0.316						
PF	0.383	0.653					
SE	0.432	0.656	0.785				
SP	0.415	0.553	0.571	0.738			
SBP	0.772	0.432	0.405	0.448	0.406		
VE	0.483	0.652	0.660	0.794	0.806	0.484	

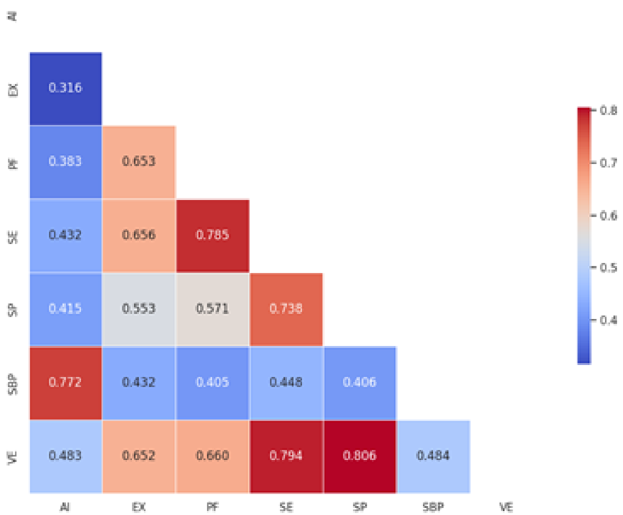


Figure 2. Heatmap Representation of HTMT Values for Latent Constructs.

Hypothesis Testing Based on the bootstrapping procedure with 5,000 resamples, the estimated path coefficients, t-statistics, and p-values demonstrated that all direct effects (H1–H7) were statistically significant. In addition, the indirect effect through mediation (H8) was also significant, as summarized in Table 5. The coefficient of determination (R^2) revealed that the model accounted for 13.9% of the variance in AI, 58.5% in self-efficacy, and 51.1% in students' behavior and performance. A more detailed interpretation of these findings is provided in the subsequent discussion section.

Table 5. Path Coefficient Result

Paths	β	Standard Deviation	T Statistics	P Values
Direct effect				
VE⇒ SE	0.190	0.064	2.941	0.003
EX ⇒ SE	0.133	0.056	2.359	0.018
SP ⇒ SE	0.256	0.064	4.022	0.000
PF ⇒ SE	0.359	0.064	5.573	0.000
SE ⇒ AI	0.373	0.066	5.607	0.000
SE ⇒ SBP	0.144	0.063	2.268	0.023
AI ⇒ SBP	0.649	0.070	9.283	0.000
Indirect effect				
VE ⇒ SE ⇒ AI	0.071	0.029	2.439	0.015
VE ⇒ SE ⇒ SBP	0.027	0.017	1.650	0.099
VE ⇒ SE ⇒ AI ⇒ SBP	0.046	0.020	2.248	0.025
EX ⇒ SE ⇒ AI	0.049	0.022	2.200	0.028
EX ⇒ SE ⇒ SBP	0.019	0.012	1.538	0.124
EX ⇒ SE ⇒ AI ⇒ SBP	0.032	0.016	2.041	0.041
SP ⇒ SE ⇒ AI	0.095	0.031	3.124	0.002
SP ⇒ SE ⇒ SBP	0.037	0.019	1.968	0.049
SP ⇒ SE ⇒ AI ⇒ SBP	0.062	0.022	2.755	0.006
PF ⇒ SE ⇒ AI	0.134	0.035	3.794	0.000
PF ⇒ SE ⇒ SBP	0.052	0.025	2.044	0.041
PF ⇒ SE ⇒ AI ⇒ SBP	0.087	0.027	3.276	0.001
SE ⇒ AI ⇒ SBP	0.242	0.057	4.227	0.000
R-square				
SE				0.585
AI				0.139
SBP				0.511
Note(s): “5,000 bootstrap samples were entered”				

Figure 3. Bootstrapping Result

3.2 Discussion

3.2.1 The Influence of Vicarious on Self-Efficacy (H1)

In the structural model, vicarious experience demonstrated a significant positive effect on self-efficacy, with a path coefficient of 0.190, thereby supporting H1. Vicarious experiences—such as observing, listening, reading, or imagining—reinforce students’ confidence in their own abilities.

In the Indonesian context, this finding is particularly relevant to English as a Foreign Language (EFL) instruction. Students who regularly engage with English-language content through television, music, or social media platforms (e.g., YouTube or X) often show greater confidence in developing language skills, particularly in writing, speaking, and listening. Such social observation provides a vicarious foundation that fosters both self-confidence and readiness for independent learning.

The significance of vicarious learning is further amplified when supported by AI. Observing peers who effectively use AI tools (e.g., Google Translate) to accomplish academic tasks can reinforce students' belief that comparable outcomes are attainable. Pedagogical approaches that integrate social modeling, peer demonstration, and AI-assisted practices therefore enhance self-efficacy, especially among Indonesian students adapting to EFL learning and emerging technologies [36].

The 2013 Curriculum in Indonesia, as discussed by Rofika et al. [37], emphasized vicarious experience as a core element of the five key pillars of learning: (1) observing, (2) questioning, (3) collecting information/experimenting, (4) associating/processing information, and (5) communicating. Observation, in particular, acts as a catalyst that equips students to address increasingly complex challenges. Although the 2013 Curriculum is no longer formally implemented, its principles remain relevant as a pedagogical reference for strengthening vicarious learning and adaptive self-efficacy in contemporary classrooms.

This continuity is reinforced by the Merdeka Belajar (Freedom to Learn) policy, which emphasizes learner autonomy, contextualized learning, and competency-based outcomes. Vicarious learning aligns closely with these principles and with the integration of AI technologies as tools for personalized and adaptive learning. Thus, while curriculum structures have evolved, the pedagogical value of indirect experience remains a robust foundation for advancing student confidence, agency, and sustainable learning outcomes.

From a practical standpoint, these findings highlight the significance of strategically integrating vicarious experiences into instructional design. Educators can design classroom activities that promote observation and collaboration [38], such as simulations, group discussions, and peer teaching. Concurrently, students should be encouraged to engage with diverse sources of knowledge, acknowledging that although the process may be demanding, it is ultimately transformative and contributes to sustained improvements in learning quality. These results align with previous research indicating that students who observe competent models tend to develop stronger self-efficacy beliefs, which subsequently enhance their academic performance [39, 40].

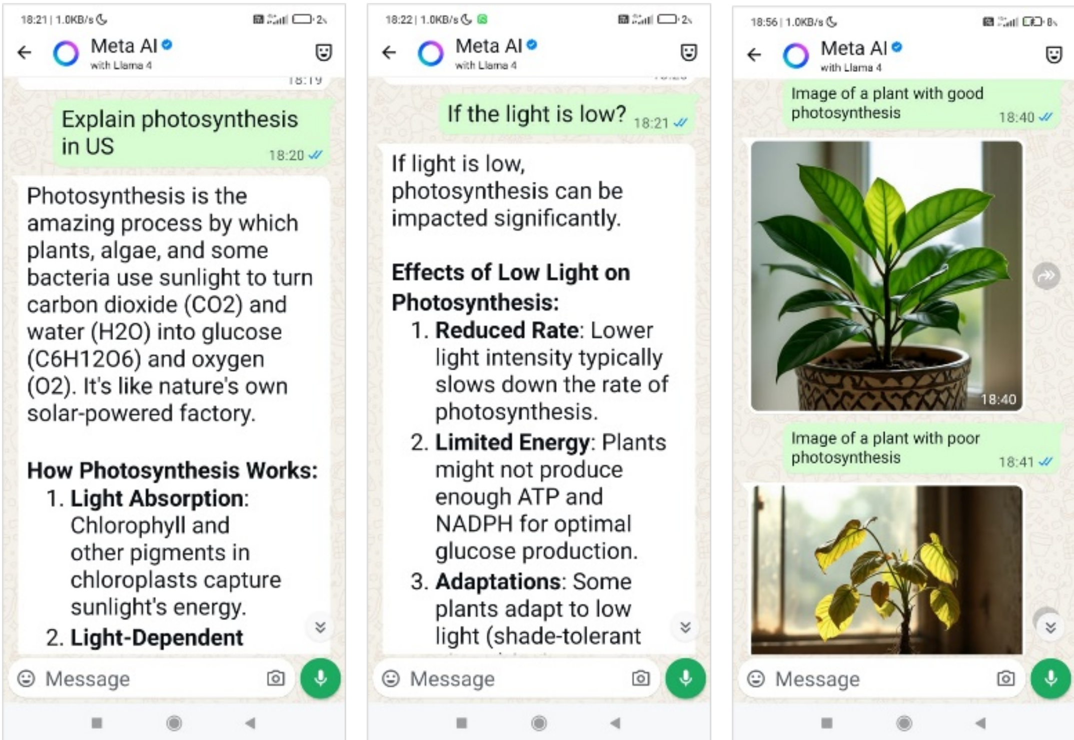
3.2.2 The Influence of Experience on Self-efficacy (H2)

The analysis revealed that the relationship between experience and self-efficacy yielded a path coefficient of 0.133. Although the effect is considered moderate, the positive direction of the relationship underscores that direct experience continues to play a crucial role in shaping learners' beliefs about their academic abilities.

The result highlights the importance for educators in Indonesia of creating learning environments that foster active exploration. Teachers should provide sufficient opportunities for learners to engage directly in the learning process, whether through classroom experiments or contextual activities outside the classroom. Learning success should not be measured solely by final grades but also by the extent of engagement and reflection demonstrated throughout the process.

For example, when students are given the opportunity to observe plant growth under varying levels of sunlight exposure in a science lesson on photosynthesis, they not only deepen their conceptual understanding but also enhance their self-efficacy through concrete and meaningful experiences. Moreover, students may be encouraged to extend their exploration of plant growth by leveraging

AI tools, such as applications integrated into WhatsApp (see Figure 4). The outcomes of these activities extend beyond conceptual mastery; they also strengthen self-efficacy through authentic and engaging experiences. Although experimental results may vary and sometimes diverge from initial expectations, the process itself makes a significant contribution to reinforcing learners' confidence.



(a) (b) (c)

Figure 4. Interaction via Meta AI

A comparable pattern was identified in the context of higher education. When university students were provided with autonomy to engage in academic tasks through approaches that encourage initiative—such as the application of the "Just Do It" principle, inspired by Nike's slogan—(https://www.nike.com/id/) —the outcomes often exceeded expectations. Student feedback indicated that authentic, hands-on experiences substantially contributed to the development of their academic self-efficacy, particularly when they were entrusted with decision-making and solving challenges independently.

Overall, the evidence reinforces the importance of instructional designs that integrate technology and promote active learner participation through both individual and group tasks. Project- and problem-based approaches involving the use of AI, as supported by prior research [41, 42, 43], represent effective strategies for enhancing self-efficacy.

3.2.3 The Social Persuasion on Self-efficacy (H3)

Social persuasion exhibited a positive effect on self-efficacy, with a path coefficient of 0.256. The result indicates that verbal encouragement, validation, and motivational support from lecturers and peers significantly shape students' beliefs in their academic competence.

Social persuasion plays a pivotal role and should be intentionally fostered by both teachers and parents. It is particularly crucial for students with lower levels of understanding, as encouragement and praise serve as powerful motivational drivers that strengthen confidence and persistence. Even simple affirmations such as "ayo semangat" ("keep going") can provide meaningful reinforcement, becoming an essential source of motivation that enhances students' self-belief. In AI-mediated learning environments, social persuasion can be embedded through digital tutor interventions [44], automated performance-based feedback, and peer-review mechanisms that reinforce learners' sense of self-worth and competence.

The relatively higher coefficient for social persuasion, compared with direct and vicarious experiences, demonstrates that social dynamics exert a stronger influence on efficacy beliefs in online and hybrid learning settings. Consequently, instructional strategies should prioritize structured social persuasion practices—such as personalized AI-generated feedback [45], systematic recognition of achievements, and the development of supportive learning communities [46]—to meaningfully enhance students' confidence and engagement in digitally mediated education.

3.2.4 The Psychological Feedback on Self-efficacy (H4)

The strong positive association between psychological feedback and self-efficacy ($\beta = 0.359$) underscores the pivotal role of affective and physiological responses in shaping students' beliefs about their academic competence. This result aligns with Bandura's [10] assertion that emotional and physiological states serve as critical sources of efficacy information, as well as Pajares' [47] observation that learners often interpret their anxiety, stress, or calmness as indicators of their ability to perform.

Psychological conditions are inherently unique to each learner, developing gradually through life experiences and developmental stages. Teachers and parents must therefore recognize and respond to these individual differences. Child-friendly school environments and supportive teachers act as key enablers of healthy psychological conditions, particularly during classroom learning. At the same time, parents play a vital role by providing continuous motivation while acknowledging both the strengths and limitations of their children. As Lindsay notes [48], when such supportive practices are implemented consistently, learners are more likely to experience psychological comfort, which in turn strengthens their self-efficacy.

Within AI-mediated learning environments, psychological feedback encompasses mechanisms designed to promote emotional regulation and resilience [49, 50]. Examples include adaptive systems that acknowledge effort, provide calming affirmations, or deliver motivational prompts tailored to learner needs. Such emotionally responsive features are especially critical in personalized digital platforms [51], where limited human interaction underscores the necessity of affective design for sustaining engagement, confidence, and long-term academic persistence.

3.2.5 The Self-efficacy on Artificial Intelligence (H5)

Self-efficacy demonstrates a moderately strong direct effect on the adoption of AI in educational contexts ($\beta = 0.373$) This suggests that students with higher academic self-confidence are more likely to engage actively and effectively with AI systems as part of their learning strategies.

Aligned with social cognitive theory, self-efficacy influences decision-making, initiative, and persistence. Learners with higher self-efficacy are more likely to adopt AI features such as analytics, personalized recommendations, and simulations, while those with lower efficacy often resist or rely passively on AI, limiting potential benefits [52, 53, 54].

In the Indonesian context, where internet access is widespread, students with strong self-efficacy confidently explore AI applications via smartphones or computers, while those with lower self-efficacy tend to hesitate. To bridge this gap, teachers and schools can implement scaffolding-based approaches that gradually build learners' confidence and provide resources aligned with their needs.

Overall, the success of AI integration in education depends not only on technological advancement but also on learners' psychological readiness. Strengthening self-efficacy through mastery-based training, social support, and constructive feedback is therefore essential to maximize the educational potential of AI.

3.2.6 The Self-efficacy on Student Behavior and Performance (H6)

The positive effect of self-efficacy on students' behavior and performance ($\beta = 0.144$) is statistically significant yet relatively weak compared to the substantially stronger effect of AI on performance ($\beta = 0.649$). This finding should not be interpreted as evidence of low self-efficacy among Indonesian students but rather as a reflection of the limited direct contribution of self-efficacy to performance in digital learning contexts. Inequities in technological access, instructional quality, and learning support may constrain its influence, as noted by Saadilah et al. [55]. Consequently, self-efficacy alone is insufficient; effective technological scaffolding is required to transform self-belief into measurable academic outcomes. In this regard, AI provides adaptive feedback, personalized resources, and collaborative opportunities, thereby strengthening learning outcomes and underscoring its role as both a critical enabler and mediator.

This interpretation is supported by both theoretical and empirical evidence. Bandura's [56] Social Cognitive Theory underscores that personal agency produces meaningful outcomes only when reinforced by environmental enablers. The Technology Acceptance Model [57] and UTAUT likewise indicate that external conditions and perceived usefulness often exert stronger direct effects on behavior and performance than psychological constructs alone. Consistent with these perspectives, Honicke and Broadbent [58] meta-analysis showed that the predictive power of self-efficacy varies across contexts, while Jeno et al. [59] found that technology-enhanced learning environments amplify its role in driving engagement. More recent studies [60, 61] further confirm that AI-based systems provide adaptive scaffolding that translates students' self-belief into tangible academic gains.

These insights are also consistent with national educational frameworks such as Indonesia's Kurikulum Merdeka and the Profil Pelajar Pancasila, which emphasize agency, persistence, and adaptability—attributes closely tied to self-efficacy. Students with higher efficacy levels tend to be more engaged and achieve stronger outcomes [62]. Accordingly, teachers, schools, and parents share responsibility for strengthening self-efficacy through mastery experiences, modelling, social persuasion, and psychological support [63], while also leveraging AI-based technologies to extend and magnify its positive effects.

3.2.7 The Artificial Intelligence on Student Behavior and Performance (H7)

The structural model demonstrates a highly significant positive effect of AI on students' behavior and performance ($\beta = 0.649$), underscoring its pivotal role in fostering academic engagement and achievement

AI literacy serves as a critical determinant of students' learning behaviors and academic outcomes. Learners who are proficient in applying AI tools gain access to diverse and relevant resources, enabling them to achieve educational objectives more effectively. Such proficiency is reflected in their ability to search, evaluate, and integrate information in line with the demands of academic tasks. By contrast, students who are less adept at leveraging AI tend to rely on conventional approaches such as textbooks or peer assistance. While these strategies retain pedagogical value, limitations in access and retrieval speed may lead to delays in task completion and reduced learning efficiency. This contrast highlights AI literacy as a vital indicator for optimizing learning performance in the digital era.

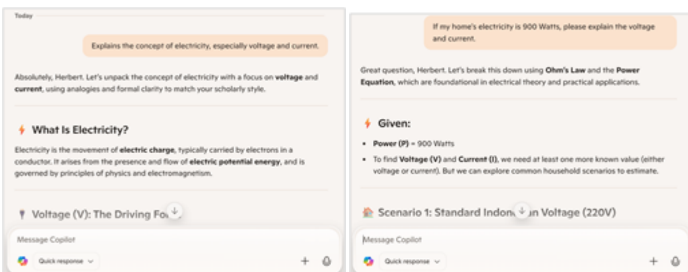
Teachers, as primary facilitators of the learning process, should systematically integrate AI into instructional design. This can be achieved through project-based activities that promote technological exploration, problem-solving, and reflective practice. For example, students may be encouraged to use AI platforms to prepare reports, analyze experimental data, or design creative solutions to local issues. The substantial effect of this pathway is consistent with emerging literature in educational technology and digital pedagogy [64]. Moreover, features such as recommendation-based learning pathways, natural language interactions with virtual tutors, and activity-log-based analytics have been shown to enhance motivation, self-efficacy, and academic outcomes [65].

3.2.8 AI mediates the relationship between Self-efficacy and Students' Learning Behavior and Performance (H8)

Beyond its direct contribution, the influence of self-efficacy on students' behavior and performance becomes substantially stronger when mediated by AI. Self-efficacy significantly predicts AI adoption ($\beta = 0.373$), and AI in turn strongly predicts student behavior and performance ($\beta = 0.649$), resulting in a mediated effect of 0.242 that surpasses the direct pathway.

These findings indicate that although self-efficacy independently influences students' behavioral and performance outcomes, its impact becomes significantly more pronounced when mediated by artificial intelligence (AI) integration. For instance, a student with high self-efficacy often exhibits heightened curiosity and a stronger inclination to explore learning resources beyond conventional materials such as textbooks or teacher-provided content. In the context of learning the concept of electricity in physics, such a student may utilize generative AI applications (e.g., ChatGPT, Copilot, Gemini) to obtain contextualized explanations and real-world applications of electricity anytime and anywhere, as illustrated in Figure 5. Through this process, AI not only expands the student's conceptual understanding but also enhances academic achievement by promoting deeper and more adaptive learning experiences. These results align with prior research emphasizing the role of AI as a pedagogical enabler that strengthens learning motivation and performance [66, 67, 68].

Moreover, the mediation effect underscores that AI functions not merely as a supportive tool but as a crucial mechanism that amplifies the influence of self-efficacy on learning outcomes, in line with recent evidence on the transformative role of educational technologies [69, 70, 71].



(a) (b)

Figure 5. Interaction via Copilot AI

In other words, the role of self-efficacy is not only direct but also indirectly reinforced through AI utilization, thereby emphasizing the pivotal role of technological mediation in optimizing student behavior and academic performance. Such insights align with the broader discourse on the integration of AI in higher education, where digital interventions have been shown to significantly reshape students' cognitive, affective, and behavioral learning dimensions [72, 73].

4. Conclusion

Consistent with theoretical expectations, the present study reveals that the relationship between self-efficacy and students' learning behaviours and performance is significantly mediated by artificial intelligence (AI). These findings highlight the pivotal role of AI in fostering adaptive learning behaviours and enhancing overall academic achievement. In doing so, the study advances the scholarly discourse on integrating psychological constructs with AI-mediated learning frameworks, particularly within the developing-country context of Indonesia.

Given Indonesia's geographic diversity, institutional heterogeneity, and disparities in technological accessibility, the study offers both theoretical and practical contributions. Theoretically, it reinforces the validity of AI as a pedagogical mediator capable of cultivating inclusive and responsive learning environments. Practically, the empirical evidence provides a foundation for policymakers to formulate AI-driven strategies that are contextually grounded, socially inclusive, and strategically aligned with efforts to strengthen student competencies in the digital era.

For policymakers, the key priorities include enhancing teachers' AI literacy through targeted professional development initiatives, establishing ethical and governance frameworks for AI use in schools, and implementing pilot programs to assess the effectiveness of AI applications in core subjects such as mathematics, literacy, and science. In this regard, the Indonesian government's introduction of Koding dan Kecerdasan Artifisial (Coding and Artificial Intelligence/KKA) represents a progressive policy initiative that necessitates systematic implementation and rigorous evaluation to mitigate regional and institutional disparities.

Beyond supporting 21st-century learning, AI also serves as a workforce-relevant instrument, enabling students not only to attain academic success but also to contribute productively to the rapidly evolving digital economy. By embedding AI-based competencies early in the learning process, education can assume a transformative role in shaping a generation capable of adaptive learning and responsive problem-solving in the face of future challenges.

Nonetheless, this study acknowledges several limitations. First, the use of purposive sampling — although appropriate for accessing students engaged in AI-related activities — constitutes a non-probability method that restricts the generalizability of the findings to Indonesia's broader student population. Second, the reliance on self-reported questionnaires may have introduced social desirability bias. Third, the exclusive use of quantitative data, while offering generalizable insights, does not fully capture the complex realities of AI integration across varied educational contexts. Factors such as school resources, teacher readiness, and regional disparities in technological access were beyond the scope of this analysis. Future research should therefore employ probability-based sampling techniques and adopt mixed-methods approaches to enhance both generalizability and depth—integrating statistical findings with qualitative insights derived from classroom practices, teacher perspectives, and student experiences.

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