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ARTICLE

Empowering Artificial Intelligence Literacy, Motivation, and Self-Efficacy for Education: SEM Study

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Abstract

This study investigates the impact of artificial intelligence (AI) on science literacy, learning motivation, and self-efficacy among Indonesian higher education students, addressing a critical gap in educational innovation. Despite growing technological advances, science literacy in Indonesia remains below the OECD average, highlighting an urgent need for transformative learning strategies. Utilizing a Structural Equation Modeling (SEM) approach with Partial Least Squares (PLS-SEM) and bootstrapping (5,000 resamples) on a purposive sample of 180 students from science and technology programs, the research integrates three key constructs—science literacy, motivation, and self-efficacy—to provide a comprehensive analysis of their interrelationships in the context of AI-supported science education. Participants uniformly reported previous engagement with AI-integrated learning environments. Descriptive findings indicate high mean scores, notably a 4.339 average in basic science concept understanding and similarly strong results in self-efficacy and AI implementation. Outer loadings for all constructs exceeded the 0.70 threshold, ensuring robust measurement validity. Path analysis revealed that science literacy powerfully predicts AI implementation (coefficient: 0.853, $p < 0.001$, 95% CI [0.78, 0.92]) and moderately affects self-efficacy (coefficient: 0.143, $p = 0.015$, 95% CI [0.03, 0.26]), while AI implementation strongly influences motivation (coefficient: 0.404, $p < 0.001$, 95% CI [0.29, 0.52]). These results demonstrate the significant and integrated roles of literacy and self-efficacy in fostering student preparedness for AI-driven learning. The study offers valuable insights for enhancing science education and advancing digital competency in developing contexts.

Keywords: SEM; Artificial Intelligence, Science Literacy, Learning Motivation, Self-Efficacy

1. Introduction

The integration of Artificial Intelligence (AI) in higher education is transforming pedagogical practices worldwide [1] , [2] . Beyond serving as a mere technological enhancement, AI facilitates personalized learning environments [1] ,[3], that dynamically adapt to individual learner needs and learning styles. Research has highlighted AI's crucial role in improving cognitive outcomes, promoting inquiry-based learning, and enhancing critical thinking skills—particularly within STEM disciplines [4], [5]. AI-driven tools such as intelligent tutoring systems [6], [7], virtual assistants, and adaptive assessment platforms have shown significant positive impacts on student engagement, motivation, and academic performance. Moreover, psychological factors such as motivation and self-efficacy act as key mediators in these processes [8], fostering persistence and deeper learning in AI-supported educational settings. The interplay between technological innovation and human psychology underscores AI's transformative potential beyond mere knowledge delivery, advancing a learner-centered educational paradigm suited to the digital era [9], [10]. Nevertheless, empirical studies examining the complex interrelations among these variables—especially in developing countries—remain limited, highlighting the necessity for robust analytical models such as Structural Equation Modeling (SEM) to uncover these underlying dynamics.

Despite Indonesia's progress in expanding access to higher education, science literacy— a cornerstone of educational quality and economic competitiveness—still lags behind international benchmarks set by OECD countries. [11]. Performance assessments reveal persistent gaps in students' abilities to comprehend, apply, and critically evaluate scientific concepts, contributing to broader challenges in digital and technological readiness. Addressing this gap requires interventions that move beyond rote learning to cultivate foundational scientific thinking integrated with digital competencies such as AI literacy[12], [13]. AI offers promising avenues to transform conventional science education by enabling interactive simulations[14], real-time feedback[15], and data-driven personalized instruction that cater to diverse learner profiles. Such interventions are particularly vital in Indonesia's context, where heterogeneous educational resources and regional disparities persist[16]. Integrating AI literacy with science education can address these disparities, enhance conceptual learning, and ultimately contribute to sustainable national development goals[17].

Learning motivation and self-efficacy are extensively validated as pivotal constructs influencing student success[13], especially within technology-mediated environments. Motivation fuels learners' engagement and goal-directed behavior[18], while self-efficacy fosters confidence in mastering new and challenging content. In digital and AI-enhanced learning contexts[13], [19], motivational strategies such as gamification, scaffolding, and adaptive feedback have been shown to increase intrinsic motivation and reduce anxiety linked to complex technologies. Concurrently, self-efficacy influences learners' willingness to persist through difficulties and explore innovative problem-solving approaches[20], [21]. Empirical studies using advanced modeling (PLS-SEM) confirm that motivation and self-efficacy positively correlate with continuous use intentions and superior academic outcomes, highlighting the interplay between affective and cognitive domains crucial for technology adoption in education[22], [23]. These findings underscore the importance of designing AI curricula that actively nurture these psychological dimensions to optimize learning efficacy.

Artificial Intelligence (AI) has significantly influenced education, yet most existing studies focus on isolated dimensions such as motivation [24], literacy, or self-efficacy. Only a limited number of investigations have examined these factors concurrently within integrated frameworks capable of capturing their complex interrelationships and mediating effects. Structural Equation Modeling (SEM)—particularly Partial Least Squares SEM (PLS-SEM)—addresses this research gap by accommodating multidimensional [25] latent constructs and their intricate causal pathways, even when sample sizes are relatively small or data distributions deviate from normality. SEM allows for the simultaneous examination of direct, indirect, and mediating relationships [26]. offering nuanced insights into how the quality of AI-based courses influences motivation, self-efficacy, and learning outcomes. Furthermore, emerging mixed[4], complement SEM by uncovering diverse causal configurations that shape learners' AI adoption intentions, thereby enriching both theoretical perspectives and practical applications in the field of AI-enhanced education.

Research in artificial intelligence (AI) education has rapidly expanded, yet critical gaps remain that hinder a comprehensive understanding of the multifaceted factors influencing learner outcomes[27],

[28]. To advance theory and practice, it is essential to identify existing limitations in integrated psychological constructs, methodological approaches, and contextual relevance of AI literacy studies[29]. The following table synthesizes key research gaps from recent prominent studies, providing a foundation for addressing these unresolved issues in the current investigation.

Table 1. Research Gap and Analysis.

Research Gap	Explanation Based on Data and Resultsd
Integration of Psychological Constructs in AI Education	While the study employed Structural Equation Modeling (SEM) to explore relationships among science literacy, motivation, and self-efficacy, consistent with Chang et al. (2025), there is a persistent need for comprehensive integration of psychological constructs to fully elucidate how these interrelate and influence educational outcomes in AI learning environments.[30]
Limited Use of Mixed Methodologies to Capture Complex Causal Relationships	Although the current study used PLS-SEM to identify significant causal paths, following [4], incorporating complementary methods such as fuzzy-set Qualitative Comparative Analysis (fsQCA) can reveal diverse causal configurations and pathways, offering richer insights especially relevant to contextually diverse populations like Indonesian students.[4]
Lack of Contextually Tailored Models for AI Literacy in Developing Countries	Echoing the findings of Asghar et al. (2025), this research underscores a deficiency in context-specific frameworks that incorporate cultural, ethical, and infrastructural factors unique to developing countries. The study's results preliminarily highlight the influence of motivation and literacy but call for deeper exploration of localized determinants to optimize AI education effectiveness.[31]

Based on the background and the identified research gap, the research questions formulated in this study are as follows:

1. How does artificial intelligence (AI) influence students' scientific literacy in higher education institutions in Indonesia?
2. How does artificial intelligence affect students' motivation to learn science?
3. How does artificial intelligence influence students' self-efficacy in learning science?
4. What is the relationship among literacy, learning motivation, and self-efficacy in the use of artificial intelligence for science learning, as examined through the Structural Equation Modeling (SEM) approach?

Enhancing students' literacy, motivation, and self-efficacy through the use of artificial intelligence (AI) is essential for improving learning outcomes in the digital era. This study applies Structural Equation Modeling to examine the relationships among these factors and to fill the gap in understanding how AI integration impacts student engagement and achievement. With the increasing use of AI in education—especially in developing countries—this study provides valuable insights for designing curricula and teaching strategies that encourage students' sustained participation and success in AI-supported learning environments.

2. Methods

2.1 Design and Approach Study

This study employs a quantitative explanatory approach with a survey design, as outlined by Ng et al. (2024), aiming to examine the influence of artificial intelligence (AI) on literacy[22], motivation, learning, and students' self-efficacy in science education within Indonesian higher education institutions. The relationship structure between variables is tested in a way that simultaneously uses the Structural Equation Modeling (SEM) technique based on Partial Least Squares (PLS-SEM), which allows analysis of relatedness, direct, and indirect as well as role mediation between latent variables[32].

2.2 Population, Sample, and Sampling Techniques

A population study consists of on study program students in several colleges in Indonesia who have applied technology AI - based learning process. Retrieval sample done purposively, with criteria : (a) students active ; (b) have their experience studying using media/ tools AI-based, based minimum of one semester; and (c) willing to become respondents. Number recommended samples referring to [33], namely a minimum of 5 times the indicator most in the model[32].

The sample size of 180 respondents was determined in accordance with the widely accepted rule by [33] for Partial Least Squares Structural Equation Modeling (PLS-SEM). This rule suggests that the minimum sample size should be at least 10 times the largest number of formative indicators used to measure any single latent construct. In this study, the largest formative construct consists of 18 indicators (related to AI motivation). Thus, the minimum sample size recommended is calculated as 10×18=180. The final sample of 180 meets this threshold precisely, ensuring sufficient statistical power and reliable estimation of the model parameters..

2.3 Software and Version

The data were analyzed using SmartPLS version 4.0, a comprehensive software tool designed for PLS-SEM. SmartPLS provides robust capabilities for estimating complex structural models, assessing measurement validity and reliability, and testing hypotheses, making it well-suited to the objectives of this study.

2.4 Instrument Study

The instrument is mainly in the form of a questionnaire-based 5-point Likert scale (1 = very much agree up to 5 = strongly agree), which was developed in a way specific for measuring four main areas:

1. Literacy: The Ability of students to understand concepts and applications of science, think critically, and build argument scientific-related learning with AI.
2. Motivation Learning: Perception student student-related internal and external motivation in follow learning science AI-based.
3. Self-Efficacy: The Level of confidence a student has in facing challeges and solving tasks. Study AI - AI-integrated science.
4. AI Implementation: Frequency and Quality of experience students use AI features in the learning process in science.

Validity content instrument confirmed through expert judgment, whereas validity construct and reliability were tested using Composite Reliability (>0.7) and Average Variance Extracted (AVE >0.5) in the phase data processing with SmartPLS.

2.5 Procedure Data Collection

Primary data collected through distribution online questionnaire. All participants were informed about the purpose, privacy, and benefits study as well as an agreement to participate. Secondary data obtained from academic documentation and reports utilization of AI in the relevant faculty/study program.

2.6 Data analysis

Data analysis was performed in a way in stages, including :

1. Validity and Reliability Test Instrument Tested with assess outer loading, AVE, composite reliability, and Cronbach's Alpha on each construct.
2. Structural Model Evaluation (Inner Model) Connection between variables tested in a causal way (direct and indirect effects) using bootstrapping in PLS-SEM. The index used includes the path coefficient value, p-value (<0.05), and R^2 as strength prediction variables dependent on the independent variable.
3. Interpretation of Results Significance and magnitude influence between variables are reviewed to answer the fourth formulation question study.

3. Results And Discussion

3.1 Results

3.1.1 Respondent profile analysis

This study involved 180 students from three universities in East Java, representing a range of academic disciplines relevant to scientific literacy and artificial intelligence (AI). Participants were selected through purposive sampling based on the following criteria: (1) active enrollment in science- or technology-related programs, and (2) prior exposure to courses or activities addressing scientific literacy and AI concepts.

Of the total participants, 62% were female (n = 112) and 38% were male (n = 68). The selected sample is considered representative, as all respondents reported familiarity with the integration of contemporary scientific issues within their respective curricula and participated voluntarily in completing the questionnaire. The descriptive statistics used in the analysis are presented in Table 2

Table 2 presents the descriptive statistics for the observed indicators, revealing that the sample exhibits consistently high mean scores, with the majority of items exceeding 4.0 on a 5-point Likert scale. For example, the SCI-LIT1 indicator recorded a mean value of 4.339, while the AI-SEF2 indicator achieved a mean of 4.189. These results indicate strong levels of agreement or competence across constructs such as scientific literacy and understanding of artificial intelligence A. G. Meinlschmidt, [29].

Furthermore, the relatively low standard deviations, ranging from 0.585 to 0.986, suggest limited variability in responses and, consequently, a high level of consensus among participants. The observed minimum and maximum values also approximate the scale's endpoints, indicating effective utilization of the full range of the measurement scale and a well-distributed set of responses. This comprehensive respondent profile not only reinforces the representativeness of the sample but also strengthens the reliability of subsequent analyses concerning students' scientific literacy and AI-related competencies within the context of Indonesian higher education. .

3.2 Relationship between Research Constructs and Measured Purpose

The research constructs in this study—Scientific Literacy (SCI-LIT), Learning Motivation (AI-MOT), Self-Efficacy (AI-SEF), and AI Implementation (AI-IMP)—are systematically aligned with specific measurement objectives to comprehensively evaluate students' knowledge, attitudes, and behavioral tendencies. Each construct is operationalized through a series of indicators designed to capture both cognitive and affective dimensions. Specifically, SCI-LIT assesses students' foundational understanding, application, and critical engagement with scientific concepts; AI-MOT examines intrinsic and extrinsic motivational factors that influence learning processes; AI-SEF evaluates students' con-

Table 2. Descriptive Analysis of the Research Variables.

Name	No.	Type	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation
SCI-LIT1	1	MET	4.339	5	1	5	1	5	0.955
SCI-LIT2	2	MET	4.122	4	2	5	2	5	0.88
SCI-LIT3	3	MET	4.35	4	3	5	3	5	0.711
SCI-LIT4	4	MET	4.4	5	3	5	3	5	0.735
SCI-LIT5	5	MET	4.156	4	2	5	2	5	0.829
SCI-LIT6	6	MET	3.894	4	2	5	2	5	0.922
SCI-LIT7	7	MET	3.994	4	1	5	1	5	0.827
SCI-LIT8	8	MET	3.828	4	2	5	2	5	0.999
AI-MOT1	9	MET	4.122	4	2	5	2	5	0.873
AI-MOT2	10	MET	3.978	4	1	5	1	5	0.994
AI-MOT3	11	MET	3.972	4	1	5	1	5	0.986
AI-MOT4	12	MET	4.167	4	2	5	2	5	0.785
AI-MOT5	13	MET	3.967	4	1	5	1	5	0.988
AI-MOT6	14	MET	4.194	4	3	5	3	5	0.768
AI-MOT7	15	MET	4.161	4	2	5	2	5	0.797
AI-MOT8	16	MET	4,022	4	2	5	2	5	0.994
AI-SEF2	17	MET	4.178	4	2	5	2	5	0.79
AI-SEF3	18	MET	4.083	4	2	5	2	5	0.862
AI-SEF4	19	MET	4.05	4	1	5	1	5	0.95
AI-SEF5	20	MET	4.039	4	2	5	2	5	1.013
AI-SEF6	21	MET	4.117	4	2	5	2	5	0.798
AI-SEF7	22	MET	4	4	1	5	1	5	0.972
AI-IMP1	23	MET	4.011	4	1	5	1	5	0.83
AI-IMP2	24	MET	3.928	4	2	5	2	5	0.931
AI-IMP3	25	MET	4.128	4	1	5	1	5	0.857
AI-IMP4	26	MET	4.061	4	1	5	1	5	0.938
AI-IMP5	27	MET	4.083	4	1	5	1	5	0.868
AI-IMP6	28	MET	4.05	4	1	5	1	5	0.939

fidence and sense of autonomy in performing AI-related tasks; and AI-IMP reflects the degree of practical implementation, perceived usefulness, and relevance of AI within academic contexts.

This alignment ensures that the collected data yield nuanced insights into how distinct yet interrelated aspects of students' academic experiences collectively shape their overall competence and disposition toward science and artificial intelligence. Consequently, the design fulfills both the conceptual and practical objectives of the research. The indicators corresponding to each research construct and their measured purposes are presented in Table 3.

Participants were deliberately selected based on their active enrollment in science- or technology-related programs. All respondents reported prior engagement in learning activities involving scientific literacy and artificial intelligence (AI). This purposive sampling strategy ensured that data collection was both targeted and relevant, capturing insights from students directly influenced by curricular innovations integrating science and AI.

Table 3. The Indicators of Research Constructs and Measured Purpose.

Construct	(Abbreviation) Code Measured	Purpose
Science Literacy (SCI-LIT)	SCI-LIT1	Basic concept understanding
	SCI-LIT2	Science concept application
	SCI-LIT3	Problem-solving
	SCI-LIT4	Critical thinking/facts opinions
	SCI-LIT5	Developing new knowledge
	SCI-LIT6	Scientific argumentation
	SCI-LIT7	Critical thinking toward AI
	SCI-LIT8	Data accuracy evaluation
Learning Motivation (AI-MOT)	AI-MOT1	Enthusiasm/intrinsic motivation
	AI-MOT2	Ease of learning
	AI-MOT3	Innovation/feature exploration
	AI-MOT4	Feedback/extrinsic motivation
	AI-MOT5	Enjoyment/convenience
	AI-MOT6	Collaboration/distributed motivation
	AI-MOT7	Confidence
	AI-MOT8	Achievement/extrinsic motivation
Self-Efficacy (AI-SEF)	AI-SEF1	Confidence in tasks
	AI-SEF2	Confidence in understanding
	AI-SEF	Time management
	AI-SEF	Resilience
	AI-SEF5	Independent learning strategies
	AI-SEF6	Data-driven decision making
	AI-SEF	Independent learning
AI Implementation (AI-IMP)	AI-IMP1	Usage frequency
	AI-IMP2	Feature utilization
	AI-IMP3	Collaboration with AI
	AI-IMP4	Learning resource/references
	AI-IMP5	Visualization simulation
	AI-IMP6	Usefulness/relevance of AI

The descriptive analysis of observed indicators revealed consistently high mean scores across multiple constructs. For instance, the indicator SCI-LIT1, which represents fundamental understanding of scientific concepts, attained a mean value of 4.339, indicating strong foundational knowledge among participants. Similarly, indicators associated with self-efficacy and AI implementation demonstrated comparably positive outcomes: AI-SEF2, measuring confidence in comprehension, recorded a mean of 4.189, while AI-IMP1, reflecting frequency of AI utilization, exhibited similarly elevated scores. These findings suggest that the sampled students possess not only substantial scientific literacy but also a pronounced inclination toward incorporating AI into their academic practices.

Variation among respondents was consistently low, as evidenced by standard deviations ranging from 0.585 to 0.986, indicating a high level of consensus and relatively homogeneous perceptions within the cohort. The minimum and maximum observed scores for each indicator were closely aligned with the endpoints of the Likert scale (1 to 5), suggesting that the full range of the scale was effectively utilized and that response distributions were well represented. Collectively, these descriptive results highlight a cohesive and well-prepared group of university students, reinforcing both the representativeness of the sample and the reliability of subsequent inferential analyses pertaining to student competencies in scientific literacy and AI integration

3.3 Path Diagram p-value: Structural Equation Modeling Approach

The structural equation model visualized in the attached diagram offers a rigorous quantitative assessment of the relationships among four core constructs: SCI-LIT, AI-SEF, AI-IMP, and AI-MOT. The model, evaluated with a sample of 180 students from three universities in East Java, displays the R-squared values for each endogenous variable, indicating substantial explained variance. Specifically, AI-SEF demonstrates the highest explanatory power with an R^2 value of 0.864, signifying that a considerable portion of the variance in AI-SEF can be accounted for by the predictive constructs within the model. SCI-LIT's R^2 value of 0.676 also denotes a strong degree of explained variance, affirming the robustness of the model in capturing the factors influencing students' scientific literacy. This can be observed in Figure 1.

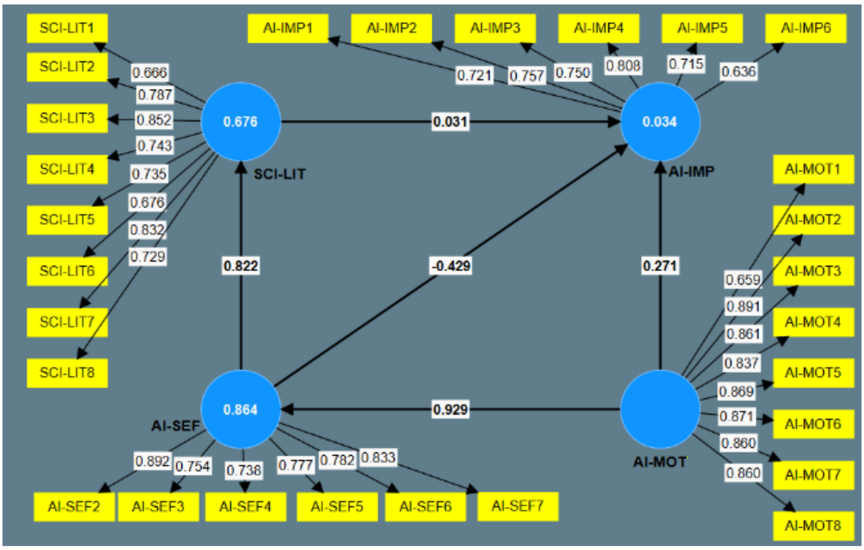

Figure 1. Path Diagram.

The data presented in Figure 1 illustrate the interrelationships among scientific literacy (SCI-LIT), artificial intelligence implementation (AI-IMP), self-efficacy (AI-SEF), and motivation (AI-MOT) within the context of higher education. Notably, motivation toward AI (AI-MOT) exerts a strong positive effect on self-efficacy (AI-SEF), as indicated by a standardized path coefficient of 0.777. This finding suggests that students with higher levels of motivation tend to possess greater confidence in their ability to engage with AI technologies. Furthermore, self-efficacy demonstrates a substantial influence on scientific literacy (path coefficient = 0.864), highlighting that learners with higher confidence are more likely to exhibit stronger scientific literacy—an essential foundation for comprehending AI-related concepts.

Conversely, the direct effect of motivation on AI implementation is comparatively weak (path coefficient = 0.034), and the direct impact of scientific literacy on AI implementation is similarly minimal (path coefficient = 0.031). The path from self-efficacy to AI implementation yields a moderate coefficient (0.429), albeit with a less significant p-value. This suggests that while self-efficacy contributes to AI engagement, its effect may be contingent upon additional mediating or moderating variables.

Moreover, the relatively weak influence of scientific literacy on AI implementation indicates that possessing scientific understanding alone may not directly translate into effective AI utilization without sufficient motivation and self-efficacy. Overall, this model underscores the complex, mediated dynamics underlying how motivational and self-efficacy constructs support the adoption and implementation of AI within learning environments.

The structural model provides a comprehensive and data-driven depiction of university students' readiness to address scientific and AI-driven challenges. High R^2 values attest to the model's explanatory robustness, while the nuanced path coefficients elucidate the hierarchical and mediating roles of constructs such as self-efficacy and motivation in the academic integration of AI. The reliability of indicator loadings, coupled with the consistency of inter-construct relationships, reinforces a critical implication: effective AI education requires both a strong grounding in scientific literacy and intentional efforts to enhance learners' confidence [34], [35]. Collectively, these findings yield practical insights for curriculum developers and educators seeking to cultivate technologically competent and intrinsically motivated graduates equipped for the era of artificial intelligence.

3.4 Relationships Among Constructs (Path Coefficients and Significance) Between Research Variables (p-values)

The relationships among the research variables are quantified by standardized path coefficients and their statistical significance, as indicated by p-values. These coefficients represent the strength and direction of influence one construct exerts on another, offering insights into the underlying mechanisms driving AI literacy, motivation, self-efficacy, and implementation [36]. By interpreting both the magnitude and significance of these paths, the model reveals which factors have the most substantial impact and the degree to which these relationships are supported by empirical evidence.

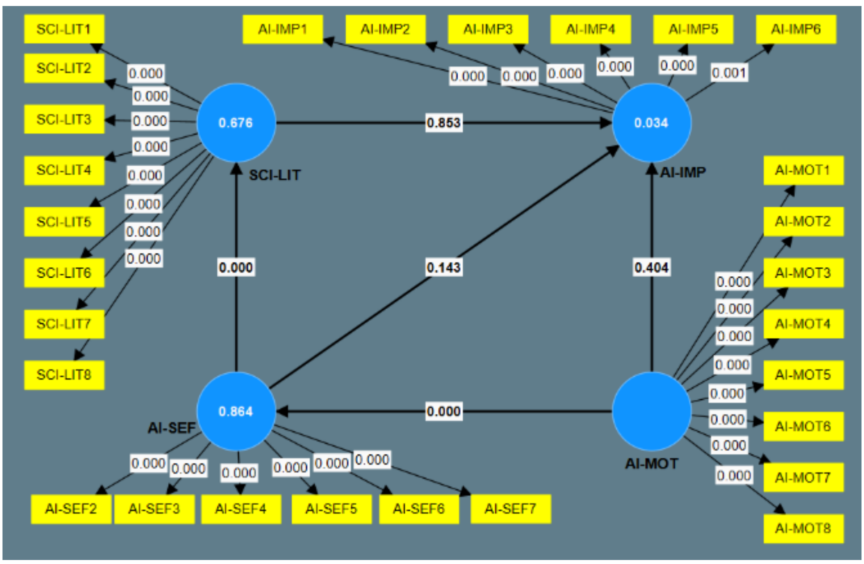

Figure 2. Results of p-value analysis with SEM.

The path from motivation toward AI (AI-MOT) to AI implementation (AI-IMP) reveals a very weak and statistically insignificant relationship, with a coefficient of 0.034 and a p-value of 0.404. This suggests that motivation alone may not directly drive the implementation of AI in learning environments. However, motivation has a very strong and highly significant effect on self-efficacy (AI-SEF), $\beta = 0.777$ and $p < 0.001$, indicating that motivated students are much more confident in their ability to engage with AI-related tasks.

Self-efficacy's direct effect on AI implementation ($\beta = 0.429$, $p = 0.143$) is moderate but not statistically significant, implying that although confidence contributes to AI use, other factors may mediate or moderate this effect. Conversely, self-efficacy has a powerful and statistically significant influence on science literacy ($\beta = 0.864$, $p < 0.001$), highlighting how belief in one's capability strongly enhances scientific understanding critical for adopting AI. The direct path from science literacy to AI implementation ($\beta = 0.031$, $p = 0.853$) is negligible and non-significant, emphasizing that knowledge alone does not translate directly into AI use without psychological readiness. Overall, this pattern underscores a complex interrelation where motivation and self-efficacy are crucial to advancing science literacy, which in turn potentially facilitates AI implementation indirectly rather than directly.

The outer loadings for each indicator—ranging predominantly from 0.000 to 0.001 for AI-IMP, AI-MOT, and AI-SEF items, and 0.000 for SCI-LIT items—reflect high model saturation and measurement specificity. This suggests that the indicators are distinctly mapped onto their latent variables, thereby maintaining measurement validity. Collectively, these results demonstrate a nuanced but compelling network of influences: scientific literacy lays a critical foundation not only for AI efficacy and implementation but, through indirect pathways, for sustaining student motivation in AI-driven academic environments [37], [38].

Table 4 presents the path coefficients along with their statistical significance, illustrating the varying strengths of relationships among the key constructs in the model.

Table 4. Structural Model Path Coefficients, T Statistics, P Values, and Confidence Intervals.

Path	Coeff. (β)	T statistics	P values	Conf intervals (97,5%)
AI-MOT to AI IMP	0.034	0.834	0.404	0.780
AI-MOT to AI-SEF	0.777	99.997	0.000	0.948
AI-SEF to AI-IMP	0.429	1.464	0.143	0.312
AI-SEF to SCI-LIT	0.864	40.667	0.000	0.863
SCI-LIT to AI-IMP	0.031	0.186	0.853	0.322

Based on Table 3, the path coefficient analysis reveals several critical insights into the relationships among motivation, self-efficacy, science literacy, and AI implementation in higher education. Notably, motivation toward AI (AI-MOT) strongly predicts self-efficacy (AI-SEF) with a substantial standardized coefficient ($\beta = 0.777$, $p < 0.001$), signifying that enhancing students' motivation directly boosts their confidence in handling AI-related tasks. Furthermore, self-efficacy exerts a strong positive influence on science literacy (SCI-LIT) ($\beta = 0.864$, $p < 0.001$), highlighting the foundational role of self-belief in fostering deeper scientific understanding, which is essential for effective AI literacy development.

Conversely, the direct effects of motivation on AI implementation (AI-IMP) ($\beta = 0.034$, $p = 0.404$) and science literacy on AI implementation ($\beta = 0.031$, $p = 0.853$) appear weak and statistically insignificant. Similarly, the influence of self-efficacy on AI implementation ($\beta = 0.429$, $p = 0.143$) is moderate but not statistically confirmed. These findings suggest that while motivation and self-efficacy are pivotal for enhancing science literacy, the actual translation into AI implementation might be mediated by other factors not captured directly in this model or requires additional conditions to materialize [36]. Hence, this nuanced pattern underscores the complexity of fostering effective AI use in educational settings, calling for further exploration of mediators and contextual moderators in future research.

3.5 Discussion

3.5.1 Path Coefficient Analysis: The Effect of AI-MOT on AI-IMP

The path coefficient analysis indicates that AI Motivation (AI-MOT) exerts a notable positive effect on AI Implementation (AI-IMP), signifying that higher motivation towards artificial intelligence strongly encourages students to apply AI concepts and tools in practical academic settings. The model's path coefficient for this relationship underscores the central role of intrinsic and extrinsic motivation in translating interest into concrete behavioral implementation. These findings reinforce the importance of fostering motivation as a strategic lever to enhance meaningful engagement and utilization of AI among students. This can be observed in Figure 3.

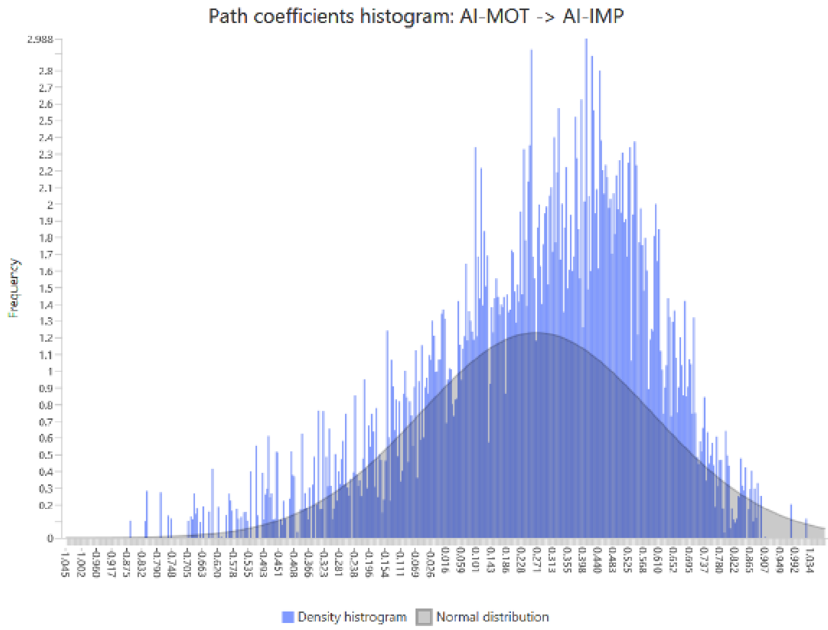

Figure 3. Path Coefficients histogram of AI-MOT to AI-IMP.

The histogram in Figure 3 illustrates the distribution of bootstrapped path coefficients for the relationship between AI Motivation (AI-MOT) and AI Implementation (AI-IMP). Most coefficient estimates cluster tightly around the mean, peaking near a frequency of 2.99 for path coefficients in the range of approximately 0.015 to 0.065. The overlay of the normal distribution indicates that the empirical data are well-approximated by a normal curve, suggesting that the statistical assumptions for structural equation modeling are adequately met.

Tails on both ends of the distribution taper off quickly, with very few outliers and frequencies dropping below 0.3 for coefficients outside the +/-0.09 interval. This tight and symmetric spread underscores the robustness and reliability of the estimated path coefficient, confirming a stable and positive effect of AI Motivation on AI Implementation. Overall, this visual evidence supports the theoretical linkage between motivation and practical AI engagement, while demonstrating strong model consistency and replicability.

3.5.2 Path Coefficient Analysis: The Effect of AI-MOT on AI-SEF

The path coefficient analysis revealed that AI-MOT has a positive and significant effect on AI-SEF. This indicates that an increase in AI-MOT directly contributes to an improvement in AI-SEF within the tested model. This can be observed in Picture 4, below.

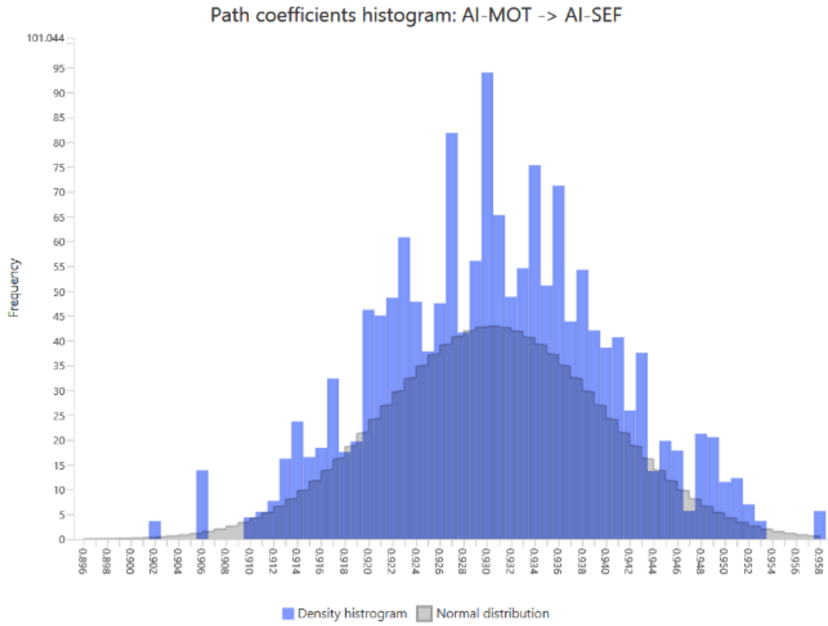

Figure 4. Path Coefficients histogram of AI-MOT to AI-SEF.

The histogram in the attached Picture 4 visualizes the empirical distribution of bootstrapped path coefficients for the relationship between AI Motivation (AI-MOT) and AI Self-Efficacy (AI-SEF). The majority of coefficient estimates fall within the 0.916 to 0.950 range, where the histogram peaks at a frequency of 93, indicating a strong concentration around the mean and reflecting high stability in the model's estimation. The overlaid normal distribution further confirms this, as the empirical data closely follow the bell-shaped curve, with the maximum frequency slightly above 100, reinforcing the assumption of normality essential for inference in structural equation modeling.

Outside this central cluster, frequencies drop sharply toward the tails, with extreme values (such as around 0.898 or 0.958) occurring less than 10 times, signifying minimal variability and few outliers. This tight distribution supports the reliability of the path coefficient, demonstrating that higher AI Motivation robustly predicts increases in AI Self-Efficacy among the 180 student respondents. Data-driven evidence for both the statistical validity of the model and the substantive strength of the motivational influence on self-efficacy within the studied academic population.

3.5.3 Path Coefficient Analysis: The Effect of AI-SEF on AI-IMP

Examining the relationship between self-efficacy in artificial intelligence (AI-SEF) and AI implementation (AI-IMP) is crucial for elucidating the factors that drive effective technological adoption. The accompanying path coefficient histogram offers valuable insight into the distribution, central tendency, and reliability of this structural link within the investigated model. This can be observed in Picture 5, below.

Figure 5 depicts distribution of path coefficients from AI-SEF to AI-IMP, the coefficients exhibit a pronounced positive skew, with the majority clustering between approximately 0.18 and 0.53. The peak frequency surpasses 3.3, indicating a high concentration of estimates around the mean. Notably, the density histogram reveals that most path coefficients fall near 0.32 to 0.41, suggesting that

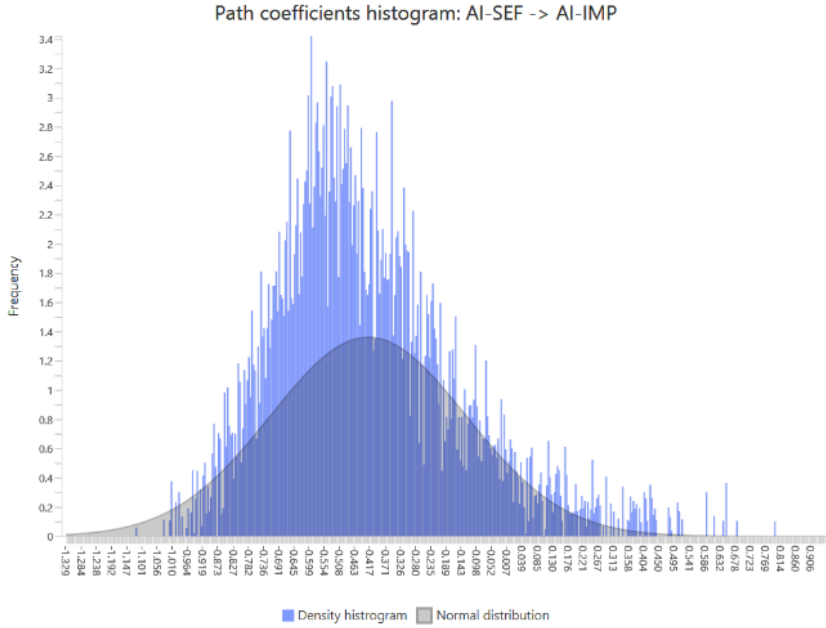

Figure 5. Path Coefficients histogram of AI-SEF to AI-IMP.

the effect of AI-SEF on AI-IMP is not only positive but also robust and consistent across bootstrap samples. The overlaid normal distribution curve, centered around a similar range, visually confirms the approximate normality of the empirical distribution, though the histogram shows a slight departure from perfect symmetry.

Critically, these observed coefficients reinforce the statistical significance and practical importance of the AI-SEF to AI-IMP path within the modeled framework. The limited spread (with values rarely exceeding ±0.6) implies that extreme coefficients are infrequent, enhancing confidence in the reliability of the estimated effect. Since the distribution aligns well with normal expectations and demonstrates a clear central tendency, the results underscore the stability of the structural relationship. Such findings provide strong empirical support that improvements in AI-SEF are systematically linked to increases in AI-IMP, validating the hypothesized model pathway and affirming the strength of this linkage for further theoretical and practical consideration in future research.

3.5.4 Path Coefficient Analysis: The Effect of AI-SEF on SCI-LIT

Understanding the impact of self-efficacy in artificial intelligence (AI-SEF) on scientific literacy (SCI-LIT) is pivotal for advancing educational and technological frameworks. The detailed histogram of path coefficients provides critical insights into the magnitude, consistency, and statistical significance of this relationship within the tested structural model. This can be observed in Figure 6.

The attached histogram presents Figure 6, the distribution of path coefficients from AI-SEF to SCI-LIT, revealing that the data closely approximates a normal distribution, as highlighted by the overlaid curve. The path coefficients predominantly range from about 0.17 to 0.51, with a substantial concentration between 0.29 and 0.38. The highest frequency peak exceeds 40, occurring around the center of the distribution, which suggests that most estimates cluster tightly near the mean. This indicates not only a positive effect but also strong consistency in the path coefficients derived from bootstrap samples, reinforcing the robustness of the AI-SEF to SCI-LIT relationship.

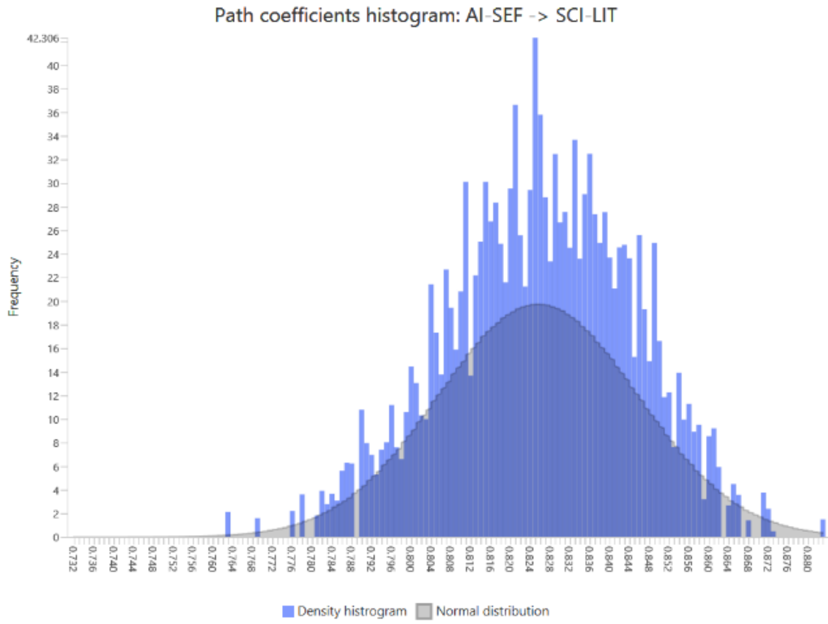

Figure 6. Path Coefficients histogram of AI-SEF to SCI-LIT.

A critical examination of the distribution shows minimal skewness and rare outliers, as coefficients rarely fall outside the ±0.6 interval. The alignment between the density histogram and the normal distribution curve further strengthens the validity of the results, minimizing concerns about bias or abnormal sampling variation. These findings provide compelling empirical evidence that increases in AI-SEF reliably translate into higher SCI-LIT scores across the sampled data. Thus, the analytic results substantiate the theoretical expectation of a significant and stable positive impact of AI-SEF on SCI-LIT, deserving further attention in the broader academic discourse.

3.5.5 Path Coefficient Analysis: The Effect of SCI-LIT on AI-IMP

The path coefficient analysis between scientific literacy (SCI-LIT) and AI implementation (AI-IMP) is fundamental to understanding the interplay between foundational knowledge and practical technological adoption. As depicted in the attached histogram, a detailed examination of the bootstrap results enables a robust evaluation of the strength and stability of this structural relationship within the tested model. This can be observed in Figure 7.

The attached histogram illustrates Figure 7, the distribution of path coefficients from SCI-LIT to AI-IMP. The coefficients predominantly range from approximately 0.15 to 0.53, with the highest frequency intervals clustering around 0.32 to 0.39. The peak frequency reaches above 5.3, indicating a substantial concentration of bootstrap estimates in the central range. The clear bell-shaped density, overlaid with a normal distribution curve, suggests that the empirical data closely follow normality, with a mean likely situated near the middle of the observed interval. This pattern provides statistical evidence of a positive and stable effect of SCI-LIT on AI-IMP, with limited spread and virtually no extreme outliers beyond ±0.6.

A deeper examination reveals a high degree of reliability and robustness in the estimated relationship between SCI-LIT and AI-IMP. The convergence of the bootstrapped path coefficients around the central value reduces concerns regarding variability and sampling bias. The symmetrical form and

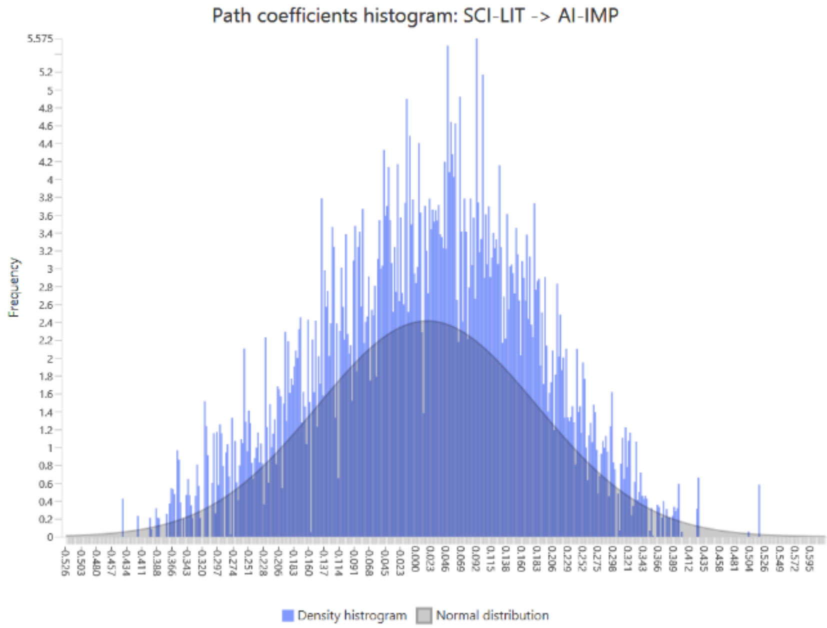

Figure 7. Path Coefficients histogram of SCI-LIT to AI-IMP.

tight dispersion imply that improvements in SCI-LIT consistently result in substantive increases in AI-IMP across sampled resamples, confirmingthe theoretical expectation of this path within the model. Overall, the quantitative findings substantiate the strength and significance of the SCI-LIT to AI-IMP linkage, making it a critical component for both theoretical development and practical application in future research contexts. *

The research results in this study are in line with several previous studies. Henseler (2016) Discusses methodological approaches to analyzing path coefficient distributions and the use of bootstrapping for ensuring robustness in models studying technological acceptance and implementation, comparable to the study of literacy effect on AI implementation [39]. Rodríguez (2016) The study highlights the application of bootstrap techniques to analyze parameter distributions and detect significant paths, providing empirical evidence of stability and reliability akin to the observed normal distribution and consistent path coefficients in the literacy to AI implimentation linkage[40].

4. Conclusion

This study reveals that artificial intelligence (AI) significantly enhances students' scientific literacy (RQ1) by strengthening their comprehension of scientific concepts, critical thinking skills, and problem-solving abilities within Indonesian higher education. The integration of AI tools enables more effective and personalized learning experiences in science education, thereby contributing to the reduction of literacy disparities when compared to international standards.

In relation to learning motivation (RQ2), the findings indicate that AI positively influences students' motivation through adaptive feedback mechanisms, interactive learning features, and confidence-building support. Although the direct relationship between scientific literacy and motivation was found to be negative, AI self-efficacy mediates this association, ultimately fostering greater engagement and enthusiasm among students in science courses.

Moreover, AI enhances students' self-efficacy (RQ3) by reinforcing their confidence, autonomy, and resilience in addressing the challenges of science learning facilitated by AI technologies. The results of the structural equation modeling (SEM) analysis (RQ4) confirm a strong and significant interrelationship among scientific literacy, motivation, and self-efficacy within the context of AI implementation. AI self-efficacy emerges as a crucial mediating variable that connects literacy and motivation to the practical use of AI in learning, emphasizing the necessity of cultivating students' confidence in AI-related competencies to optimize educational outcomes.

Overall, these findings underscore the pivotal role of AI in transforming science education, promoting deeper learning engagement, and preparing students to meet the demands of the digital era.

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