E-ISSN: 2964-3171
P-ISSN: 2985-3214

JUPITER Volume 03 Nomor 03 September 2025

The Effect Of Ai Literacy, Ethics, And Motivation on Student Learning Gains

Shofiyah Rosyadah[1], Ahmad Siddiq Mappatunru[2], Aprilianti Nirmala S[3*], M Miftach Fakhri[4]

Universitas Negeri Makassar[1234]
Corresponding e-mail: nirmalaaprianti@gmail.com

Received: 04 Juli 2025
Accepted: 27 Agustus2025
Published: 9 September 2025

ABTRACT

The increase in the use of artificial intelligence (AI) in higher education is happening faster than the readiness of literacy and ethical frameworks, thus creating a need to understand the factors that influence the effectiveness of AI utilization on student learning outcomes. This study aims to examine the influence of AI Literacy, AI Ethical Awareness, and Motivation to Learn with AI on Learning Gains and to identify the most dominant predictors. The study used a cross-sectional quantitative design with a sample of university students in Makassar selected through purposive sampling. The measurement of motivation adapted some items from the Academic Motivation Scale (AIMS) that had been psychometrically tested prior to structural analysis. The model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results showed that the three independent variables had a positive and significant effect on Learning Gains, with coefficients $\beta = 0.208$ for AI Literacy, $\beta = 0.236$ for AI Ethical Awareness, and $\beta = 0.358$ for Motivation to Learn with AI. The R^2 value of 0.532 indicates the model's explanatory power in the moderate category. The f^2 effect size shows that motivation makes the largest contribution (0.329), while AI Literacy and AI Ethical Awareness have a small effect. Thus, motivation emerges as the strongest predictor, confirming that the successful integration of AI in learning depends not only on technical competence and ethical awareness, but also on the affective dimension of students. These findings contribute to the development of AIED studies and motivation theory, and emphasize the importance of educational strategies that balance literacy, ethics, and motivational support.

Keywords: AI literacy, Ethical awareness, Higher education, Learning motivation, Learning gains

INTRODUCTION

Artificial intelligence in education is developing rapidly and raises important questions about its impact on the cognitive, affective, behavioral, social, and ethical domains of users (Sutabri et al., 2025) These developments create new vulnerabilities related to academic integrity, privacy, and learning equity, making the need for AI literacy and ethical governance in higher education increasingly urgent (Sutabri et al., 2025; Wadmany & Davidovitch, 2025) The imbalance between the high level of GenAI utilization, which reaches 92% of students (Freeman, 2025), and the low availability of official policies in educational institutions, which is still below 10% (GEM Report Team, 2023). indicates variations in knowledge, ethics, and motivation for AI use that can affect learning outcomes. Furthermore, the direct relationship between AI literacy and academic performance still shows inconsistent findings (Bećirović et al., 2025), requiring more targeted correlational studies before formulating problem identification in the context of Indonesian students.

The use of AI by Indonesian students is increasing rapidly without being accompanied by an adequate literacy and ethics framework. The AI literacy framework emphasizes conceptual understanding, technical skills, and critical assessment, but research shows that the path from AI literacy to academic performance is often insignificant even though it is related to self-efficacy(Bećirović et al., 2025). In the realm of ethics, there is no single theory that explains student behavior in using AI, resulting in diverse patterns such as questionable use that is still considered to improve performance (Wadmany & Davidovitch, 2025). The motivation to use AI also shows the potential to increase interest and personalize learning, but this tendency has not been comprehensively tested against multidimensional learning outcomes (Badarudin et al., 2024). This condition indicates the need for a more systematic reading of the relationship between these three constructs in the context of higher education.

To date, the relationship between the components of AIED AI literacy, AI use ethics, and motivation with learning outcomes is still not well established. Some studies even report that all paths to academic performance are insignificant (Bećirović et al., 2025). Limitations in design, such as the dominance of cross-sectional surveys and convenience sampling, weaken external validity and limit a comprehensive understanding of these constructs. More importantly, there are almost no studies that simultaneously test these three variables in a single model on student learning outcomes (Wadmany & Davidovitch, 2025). This is the main research gap: the lack of an integrated conceptual model that tests how AI literacy, ethics, and motivation contribute simultaneously to student learning outcomes. This gap needs to be addressed, especially in the context of Indonesian universities, which are in a phase of rapid GenAI adoption.

The urgency of this research stems from the need to systematically understand how AI literacy, AI use ethics, and AI use motivation contribute to student learning outcomes. In a situation where the use of AI is growing rapidly but is not yet balanced by adequate academic and ethical understanding, empirical mapping is needed to explain the influence of these three aspects on the dimensions of learning outcomes measured using AUSSE Learning Gains, which include General Education, Personal & Social Development, and Practical Skills. This study places these three constructs in a correlational model to examine the strength and direction of the relationships formed, thereby providing a more complete picture of the role of AI in the student learning process.

This study aims to estimate the relationship between AI literacy, AI use ethics, and AI use motivation with student learning outcomes measured through AUSSE Learning Gains. Specifically, this study examines the relationship between AI literacy and the three domains of learning outcomes, explores the relationship between AI use ethics and the three domains, and analyzes the relationship between AI use motivation to determine the variables that have the most dominant influence. The findings are expected to provide an empirical basis for the development of campus policies and learning strategies that balance personalized learning, academic integrity, and ethical governance of GenAI use.

RESEARCH METHOD

Research Design

This study uses a **quantitative** method **with a *cross-sectional* design.** This design was chosen because it allows researchers to describe and analyze the relationship between three independent variables, namely AI literacy, AI ethical awareness, and motivation to learn with AI, and the dependent variable(Creswell & Creswell, 2017) namely students' academic learning outcomes. A *cross-sectional* approach means that all variables are measured once in a certain period without manipulation or intervention, so that the relationships found are associative, not causal. This design is in line with the research objectives, which emphasize mapping the relationships between variables in the natural context of AI use in a university environment.

Participant

The participants in this study were active university students in Makassar who had used AI technology in their learning activities. The sampling technique used was purposive sampling, because the selection of respondents was based on certain characteristics relevant to the research objectives, namely experience using AI in an academic context. The inclusion criteria were: (1) active undergraduate students, (2) having experience using generative AI such as ChatGPT, Copilot, Gemini, or similar platforms to complete academic assignments, and (3) willing to participate voluntarily by filling out an online questionnaire. This approach allows researchers to obtain a group of participants that suits the needs of analyzing the relationship between AI literacy, ethical awareness, motivation, and learning outcomes.

Population and the Methods of Sampling

Detailed data on the number of active undergraduate students by field of study or institution in Makassar City is not publicly available. However, data from the Makassar City Statistics Agency in 2025(BPS Sulawesi Selatan, 2025) shows that the total number of students in this city reached 266,778, confirming its position as the largest center of higher education in eastern Indonesia. The high number and diversity of students reflect a highly heterogeneous academic population.

Given the extensive and varied population conditions, purposive sampling is considered the most appropriate approach. The selection of respondents focused on students who met the criteria for using AI technology in learning, resulting in a sample that was appropriate for the research variable analysis requirements. The use of this technique is also appropriate in situations where the sampling frame cannot be fully identified because students are spread across various institutions with different levels of AI utilization. To ensure participant eligibility, the online questionnaire included screening questions related to AI usage experience.

Instrument

This research instrument was designed to measure four main variables related to the use of Artificial Intelligence (AI) in learning, namely AI Literacy, AI Ethical Awareness, Motivation to Learn with AI, and Learning Gains. Each indicator was developed based on literature reviews and previous studies to suit the context of technology-based higher education. The AI Literacy variable assesses students' ability to understand, evaluate, and use AI critically, while AI Ethical Awareness emphasizes awareness of privacy, algorithmic fairness, and ethical responsibility in its use. Motivation to Learn with AI describes students' drive to learn and experiment with AI technology, while Learning Gains measures perceptions of improvements in learning and analytical thinking skills. All items use a 4-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Agree, 4 = Strongly Agree) to obtain clear responses without neutral options.

Table 1. Research Instrument

Variable	Item	Statement	Reference
AI Literacy	AI-L1	I can choose the Artificial Intelligence (AI) technology that best suits the type of task I am working on.	(B. Wang et al., 2023)
	AI-L2	I can use basic AI features (e.g., composing prompts) to support learning.	
	AI-L3	I verify the accuracy of AI outputs by comparing them to reliable reference sources before use.	
	AI-L4	I assess whether AI outputs are relevant to the purpose and context of the task, then edit them to ensure they are appropriate before submission.	
	AI-L5	I can recognize and correct bias (partiality/unfairness) and hallucinations (incorrect/fabricated information) in AI outputs.	
AI Ethical Awareness	AI-EA1	I assess that AI needs to learn from diverse data to ensure its results are unbiased and impartial.	(Z. Wang et al., 2025)

	AI-EA2	I believe it is important for AI to explain the reasoning behind its recommendations or decisions so that users can understand them.	
	AI-EA3	I believe it is important for users to receive education on AI ethics issues to prevent misuse.	
	AI-EA4	I consider it important for privacy to be protected when AI processes personal data.	
	AI-EA5	I believe there should be clear mitigation procedures in place if AI causes harmful effects.	
Motivation to Learn with AI	MLW-AI1	I learn with AI because I enjoy the process and am curious to try out its features.	(Li et al., 2025)
	MLW-AI2	I learn with AI because I believe that using AI helps me achieve my study goals and prepare for my career.	
	MLW-AI3	I learn with AI because I would feel guilty or left behind if I didn't use it.	
	MLW-AI4	I learn with AI because there are demands or requirements from professors or institutions.	
	MLW-AI5	I don't see a clear reason why I need to study with AI. (*reverse score)*	
Student Learning Gains	LG1	I feel that my ability to understand and explain the core concepts of the course has improved.	(Tadesse et al., 2018)
	LG2	I feel that my ability to synthesize multiple readings into a clear and easily understandable argument has improved.	
	LG3	I feel that my ability to write assignments or reports with proper structure and citations has improved.	
	LG4	I feel that my ability to assess the reliability and accuracy of information before using it has improved.	
	LG5	I feel that my ability to apply theory to solve problems or cases has improved.	

Although the Academic Motivation Scale (AIMS) was theoretically developed as a multidimensional construct based on Self-Determination Theory (Deci & Ryan, 1985), the adaptation of the instrument in this study only produced one indicator for each form of motivation regulation. This condition does not meet the minimum psychometric prerequisites for multidimensional modeling, because a model with one indicator per dimension does not allow for adequate estimation of measurement error and risks producing unstable parameters and unidentified factor models (Hair et al., 2020; Kline, 2015; Morin et al., 2016).

Referring to the SDT view that motivational regulation exists on a gradual autonomy-control continuum and can be represented as a general level of motivation in a specific context (Deci & Ryan, 1985; Vansteenkiste et al., 2020), the construct of motivation to learn with AI is treated as a global representation of AI-based learning

JUPITER
JURNAL PENDIDIKAN TERAPAN

E-ISSN: 2964-3171
P-ISSN: 2985-3214

JUPITER Volume 03 Nomor 03 September 2025

motivation and modeled unidimensionally in accordance with the operational reality of the adaptation instrument. This decision was validated through Exploratory Factor Analysis (EFA) to assess the pattern of indicator loadings, followed by Confirmatory Factor Analysis (CFA) to evaluate the suitability of the one-factor model (DeVellis & Thrope, 2021; Knekta et al., 2019). This approach was applied specifically to the motivation construct because only this construct underwent structural changes due to adaptation, so that a re-examination of the internal structure was necessary to ensure operational validity before use in PLS modeling (Putnick & Bornstein, 2016; Worthington & Whittaker, 2006).

Procedures

The research procedure began with the development and content validation of instruments covering three main constructs, namely AI literacy, ethical awareness of AI use, and motivation to learn with AI. The questionnaire was distributed online through social media, student groups, and academic forums on campus. Before filling out the questionnaire, participants first read and agreed to an informed consent form that explained the purpose of the study, the voluntary nature of participation, and the guarantee of data confidentiality. The order of items in the questionnaire was randomized to minimize common method bias and was supplemented with attention check items to ensure data quality. After collection was complete, the data was downloaded into a spreadsheet format and then imported into SmartPLS for measurement model and structural model analysis.

Analysis Plan

Data analysis in this study was conducted in two main stages, namely descriptive analysis and inferential analysis. In the descriptive analysis stage, the data was processed using Jamovi to describe the characteristics of the respondents. Before entering into inferential analysis, the construct structure of the AIMS adaptation variables was tested through PCA/EFA analysis in Jamovi to assess whether the indicators had the potential to form a stable dimension. The inferential stage was then carried out using SmartPLS with the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which included evaluation of the measurement model (outer model) and structural model (inner model). The outer model evaluation included testing convergent validity (loading factor ≥ 0.70 and AVE ≥ 0.50), discriminant validity (Fornell–Larcker criteria and cross-loading), and construct reliability through Composite Reliability and Cronbach's Alpha. Hypothesis testing was conducted using the bootstrapping procedure at a significance level of $\alpha = 0.05$, and the relationship between variables was considered significant if the p-value was < 0.05. This series of analyses was chosen because it was able to support the correlational research objectives in identifying and measuring the strength of the relationship between latent constructs in the model.

RESULTS AND DISCUSSION

Demographic Analysis of Respondent

Demographic analysis is presented to provide context regarding the characteristics of students from universities in Makassar who were sampled in this study. The majority of respondents came from non-STEM fields, reflecting the humanities and social sciences academic orientation common at these institutions. Because this study used purposive sampling, the descriptive analysis was not intended to generalize the student population at large, but to clarify the profile of the sample used in mapping the relationship between AI literacy, AI use ethics, motivation to learn with AI, and student learning outcomes.

Table 2. Respondent Characteristics

Characteristic	**N**	**Percentage**
Gender		
Male	52	42.6
Female	70	57.4
Total	122	
Age		
17 Years	2	1.6%
18 years	17	13.9
19 years	61	50.0
20 years	22	18.0
21 Years	8	6.6
22 Years	6	4.9
23 Years	5	4.1
25 Years	1	0.8%

JUPITER JURNAL PENDIDIKAN TERAPAN

E-ISSN: 2964-3171
P-ISSN: 2985-3214

JUPITER Volume 03 Nomor 03 September 2025

Semester		
I	19	15.6%
III	83	68.0
V	9	7.4
VII	11	9.0
Major		
STEM (Biology, Physics, Chemistry, Engineering, Mathematics)	52	42.6
Non-STEM (Humanities, Economics, Accounting, Management, Psychology, Arts, Health and Welfare, Education)	70	57.4
Frequency of AI Use for Academic Purposes		
Less than once a week	5	4.1%
About once a week	17	13.9
Almost every day	62	50.8
Every day	38	31.1

Based on Table 2, the demographic pattern shows that the group of first-year students has relatively homogeneous age and semester characteristics, thus providing a stable context for the correlational relationship analysis that is the focus of this study. This homogeneity does not pose a methodological problem because the study does not aim to make population inferences but rather to test the direction and strength of the relationships between variables in the PLS-SEM model. Thus, the limitations of demographic variation are within acceptable limits and do not affect the validity of the estimation of the relationships between literacy, ethics, and motivation to use AI with the three domains of learning outcomes measured through AUSSE Learning Gains.

Explanatory and Confirmatory Factor Analysis

In the initial stage of exploratory analysis, the MLW-AI1 item showed unreasonable estimates and raised a Heywood case, which generally indicates model misspecification or indicator instability, making it unsuitable for retention in the factor structure (Kline, 2015). Given the risk this posed to measurement accuracy, this item was excluded from further analysis to maintain the accuracy of construct representation. After this refinement, the results of Exploratory Factor Analysis (EFA) in Table 3 showed that the remaining indicators formed a relatively stable structure centered on one main factor. The loading pattern that emerged illustrates the consistent contribution of most items, while one indicator with a more moderate loading was retained due to its conceptual relevance to the domain of motivation—in accordance with the principle that indicators with important theoretical weight should be retained even if their statistical contribution is low (Clark & Watson, 2019; DeVellis & Thrope, 2021).

Table 3. Exploratory Factor Analysis (Final Structure After Item *Refinement)*

Item	Factor Loading	Uniqueness	Item KMO	Decision
MLW-AI2	0.484	0.766	0.866	Marginal
MLW-AI3	0.814	0.337	0.746	Maintained
MLW-AI4	0.753	0.433	0.774	Maintained
MLW-AI5	0.745	0.445	0.771	Maintained

Based on the results in Table 3, the data feasibility results support the interpretation of an acceptable single factor structure and do not indicate dimensional fragmentation. This pattern indicates essential unidimensionality, which is a condition where one common factor dominates the variance of the construct despite minor variations between indicators (Reise, 2012; Rodriguez et al., 2016). Thus, the construct of motivation to

E-ISSN: 2964-3171
P-ISSN: 2985-3214

JUPITER Volume 03 Nomor 03 September 2025

learn with AI shows sufficient internal consistency as a single factor representing learning motivation in the context of AI use.

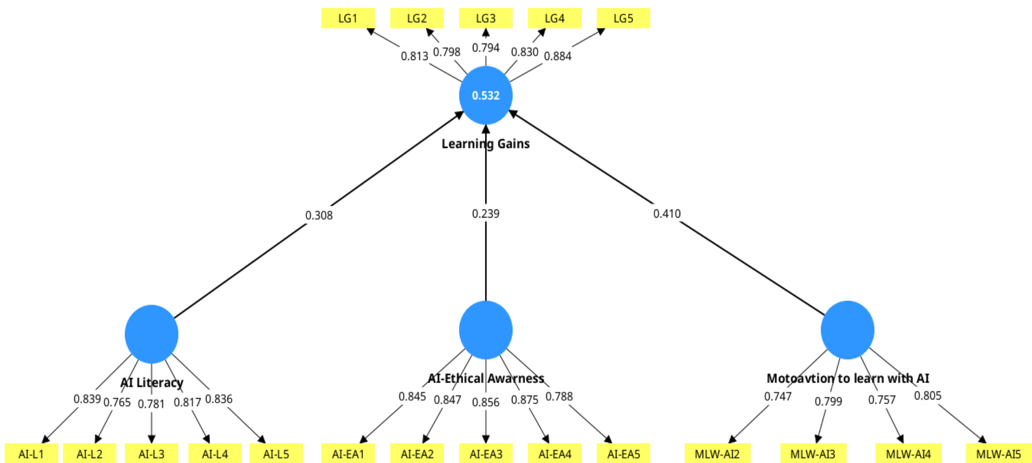
Table 4. Confirmatory Factor Analysis – Model Fit Summary

Index	Value	Criteria	Interpretation
χ^2 (df)	0.325 (2)	-	Not significant
p-value	0.850	>0.05	Model fit
RMSEA	0.00	<0.08	Very good
CFI	1.00	>0.90	Very good
TLI	1.04	>0.90	Very good
SRMR	0.007	<0.08	Very good

Furthermore, the results of Confirmatory Factor Analysis (CFA) in Table 4 confirm these exploratory findings. All model fit indices are in the excellent range, including CFI and TLI, which exceed the 0.90 threshold, and RMSEA and SRMR, which are below the conservative threshold, indicating that the one-factor model has a strong global fit (Hu & Bentler, 1999; Schreiber et al., 2006). The consistency between the EFA and CFA results provides empirical support that the construct structure is stable and coherent, making it appropriate to treat it as a unidimensional construct at the measurement model evaluation stage in PLS-SEM analysis.

Measurement Model Evaluation

This section evaluates the quality of the measurement model before structural model analysis is performed. The outer model evaluation aims to ensure that each indicator is able to represent the latent construct accurately and consistently. The assessment is carried out by examining outer loadings, internal reliability, convergent validity, and discriminant validity, in accordance with the best practice recommendations in the latest PLS-SEM (Hair et al., 2020).



Gambar 1. Structure Model

The measurement model used in this study includes four latent constructs, namely AI Literacy, AI Ethical Awareness, Motivation to Learn with AI, and Learning Gains. The first three constructs act as predictors directed at Learning Gains as the dependent variable. This framework reflects the conceptual relationship that describes how AI literacy, ethical awareness, and motivation to learn with AI contribute to improving student learning outcomes. The presentation of this conceptual model provides a clear basis for empirical testing and is in line with the contemporary PLS-SEM approach, which emphasizes the importance of clarity in causal relationships before structural interpretation is carried out (Hair et al., 2020).

Before examining the relationships between constructs in the structural model, the measurement model was first evaluated to ensure the quality of the indicators' representation of the constructs. This evaluation included examining outer loadings, Average Variance Extracted (AVE), Composite Reliability (CR), Cronbach's alpha, and rho_A to assess the convergent validity and internal consistency of each construct. In addition, discriminant validity is also tested to ensure that each construct has clear conceptual boundaries and can be distinguished from one another. This procedure is a crucial step in modern PLS-SEM to ensure that the estimation of structural relationships is based on valid and reliable constructs (Hair et al., 2020; Henseler et al., 2015).

Table 5. Convergent Validity and Construct Reliability

Construct	Loading (min-max)	AVE	CR	Cronbach's α	ρA	VIF
AI Literacy	0.765-0.839	0.653	0.904	0.867	0.872	2.198
AI Ethical Awareness	0.788-0.875	0.710	0.924	0.898	0.900	2.002
Motivation to Learn With AI	0.747-0.805	0.604	0.859	0.789	0.807	1.093
Learning Gains	0.794–0.883	0.680	0.914	0.882	0.890	

The test results show that the loading values range from 0.614 to 0.883, with most exceeding the threshold of 0.70. The AVE values range from 0.534 to 0.710, indicating that convergent validity is fulfilled. Internal reliability is also adequate, as reflected in the CR and Cronbach's alpha values, which are above the minimum threshold. All VIF values are < 3, indicating no multicollinearity, while the HTMT values range from 0.295 to 0.799, indicating that discriminant validity is fulfilled.

To complement the reliability test, the rho_A value was analyzed together with the confidence interval (CI) to assess the stability of internal construct consistency through the resampling process. The entire CI range was above the recommended minimum threshold, so that construct reliability was assessed as stable and insensitive to sample variation. This approach reinforced the previous reliability results and ensured that construct estimates remained consistent under various analysis conditions (Henseler et al., 2015)

Table 6. Composite Reliability (ρA) and Confidence Interval

Construct	Original ρA	Sample (M)	Mean	5% CI	95% CI	Interpretation
AI Ethical Awareness	0.900	0.902		0.866	0.932	Highly reliable and stable
AI Literacy	0.872	0.872		0.824	0.910	Highly reliable and stable
Learning Gains	0.891	0.808		0.846	0.929	Highly reliable and stable
Motivation to Learn With AI	0.807	0.808		0.718	0.878	Reliable and stable

Based on the results presented in Table 6, the reliability evaluation using Composite Reliability (ρA) shows that all constructs have good and stable internal consistency. The constructs of AI Ethical Awareness, AI Literacy, and Learning Gains are in the highly reliable category, which indicates that the indicators in each construct are able to measure the concept consistently and accurately. Meanwhile, the Motivation to Learn with AI construct also shows adequate reliability, although slightly lower than the other constructs, but still within acceptable limits. The relatively controlled Confidence Interval (CI) range across all constructs shows that the reliability values obtained are stable and do not show significant fluctuations, thus reinforcing the belief that the instruments used have good measurement stability and are suitable for supporting further structural model analysis.

After verifying reliability consistency, discriminant validity was evaluated to ensure that each construct had clear conceptual boundaries and did not overlap with other constructs. The results of the Fornell–Larcker test in Table 7 show that the AVE root value of each construct is higher than its correlation with other constructs, indicating adequate conceptual separation. This finding confirms that the constructs are able to stand as distinct entities from one another in the measurement model [14].

Table 7. Fornell-Larcker Discriminant Validity

	AI Literacy	AI Ethical Awareness	Learning Gains	Motivation to Learn With AI
AI Literacy	0.808			
AI Ethical Awareness	0.707	0.843		
Learning Gains	0.596	0.528	0.824	
Motivation to Learn With AI	0.288	0.173	0.541	0.777

Based on Table 8, the HTMT test results further strengthen the fulfillment of discriminant validity in the measurement model. All construct pairs show a level of relationship that is within acceptable limits, indicating no excessive correlation or conceptual overlap between latent variables. This shows that each construct measures different aspects empirically and is not redundant with one another. Given that HTMT is known as a more sensitive approach in detecting potential discriminant validity issues, these findings provide strong support that the construct structure in the model has been clearly defined and has adequate conceptual differentiation, so that the measurement model can be declared feasible and robust to proceed to the structural model evaluation stage.

Table 8. HTMT Discriminant Validity

Construct pair	**HTMT**
AI Ethical Awareness ↔ AI Literacy	0.799
Learning Gains ↔ AI Literacy	0.666
Learning Gains ↔ AI Ethical Awareness	0.587
Motivation to Learn With AI ↔ AI Literacy	0.327
Motivation to Learn With AI ↔ AI Ethical Awareness	0.190
Motivation to Learn With AI ↔ Learning Gains	0.598

Overall, the reliability and discriminant validity results show that all constructs in the measurement model have good internal consistency, concept separation, and estimation stability. With all outer model criteria met, the analysis can proceed to structural model testing.

Structural Model Evaluation

The analysis then proceeded to the structural model evaluation stage to assess the strength of causal relationships between latent constructs and the contribution of each exogenous variable to Learning Gains. The testing was conducted through a bootstrapping procedure with 5,000 resampling to obtain stable and reliable path estimates, as recommended in current PLS-SEM practice (Hair et al., 2020). The test results presented in Table 9 show that all structural paths have a positive and significant direction of influence, indicating that improvements in AI literacy, ethical awareness, and AI-based learning motivation correlate with improvements in student learning outcomes.

Table 9. *Path Coefficients and Confidence Interval*

Relationship	**β**	**t-value**	**p-value (one-tailed)**	**5% CI**	**95% CI**	**Interpretation**
AI Literacy → Learning Gains	0.208	2.731	0.003	0.080	0.356	significant
AI Ethical Awareness → Learning Gains	0.236	2.771	0.003	0.063	0.426	significant

Motivation to Learn With AI → Learning Gains	0.514	5.197	<0.001	0.359	0.676	Significant

After all path coefficients were proven significant through the previous analysis, the model evaluation stage continued by assessing the explanatory power of R^2 and the effect size of f^2 of the model. Based on Table 10, the R^2 value is in the moderate to high category, indicating that the exogenous variables are able to explain a substantial proportion of the variance in learning outcomes as categorized in the PLS-SEM literature (Hair et al., 2020) .

Table 10. Evaluation of Model Predictive Power Based on R^2 and f^2

Relationship	f^2 (Effect Size)	f^2 Category	R^2 (Learning Gains)	Category R^2	Description
AI Literacy → Learning Gains	0.096	Small	0.532	Moderate	Small effect
AI-Ethical Awareness → Learning Gains	0.061	Small	0.532	Moderate	Small effect
Motivation to Learn with AI → Learning Gains	0.329	Large	0.532	Moderate	Large effect

In addition, the effect size f^2 in Table 10 shows differences in contribution between constructs, where some predictors have a small effect, while one construct shows a large effect that marks its position as the main predictor (Hair et al., 2020; Henseler et al., 2015). Overall, the combined evaluation of R^2 and f^2 in Table 10 not only confirms that the model has strong structural validity and explanatory power, but also reveals which constructs have the most substantial influence on learning outcomes.

Discussion

This study shows that the three main variables, namely AI Literacy, AI Ethical Awareness, and Motivation to Learn with AI, are positively related to Learning Gains, with motivation being the strongest predictor. These findings confirm that the successful integration of AI in learning does not only depend on technical competence or ethical understanding, but also on the psychological drive that makes students willing to use AI actively and continuously. In this context, motivation acts as an internal mechanism that directs how and to what extent students utilize technology to support their learning process [13], [17].

These findings deepen the results of previous research that reported inconsistencies in the direct relationship between AI literacy and academic performance (Bećirović et al., 2025). These inconsistencies can be understood because literacy, although important, does not automatically encourage intensive use of technology if it is not supported by psychological motivation. Ethics also plays an interesting role: research such as (Wadmany & Davidovitch, 2025) shows that ethical awareness does not necessarily reduce the use of AI, but rather structures how users interpret its benefits and limitations. In this context, ethics functions more as a normative compass than a driver of behavior. In comparison, motivation has the strongest effect because it directs psychological energy and determines whether the abilities and knowledge possessed will be manifested in AI-based learning behavior (Zhai & Nezakatgoo, 2025).

Theoretically, these findings provide important confirmation that affective variables, particularly autonomous motivation, are a determining mechanism in explaining the relationship between AI use and improved learning outcomes. Its dominant effect reflects that learning technology does not work automatically; technology only has an impact when individuals have aligned interests, goal orientations, and perceptions of benefits. This perspective is consistent with studies showing that AI interventions are more effective when they combine technical and psychological aspects of students (Costello et al., 2025; Kasneci et al., 2023). Thus, the theoretical contribution of this study not only confirms existing models but also highlights the importance of placing motivation at the center of research in the domain of AI-enabled learning.

This study has several limitations that should be noted. First, the use of a purposive sample from a single institution reduces the generalizability of findings, a limitation common in educational technology-based studies. Second, the Motivation to Learn with AI construct uses a limited adaptation of items, so that although it is empirically valid, it does not yet fully reflect the broad spectrum of motivational regulation. Third, the cross-sectional design limits causal inference, while longitudinal studies have been recommended to capture the motivational dynamics in the use of learning technology.

Future research should expand the population coverage so that findings on AI literacy, ethical awareness, and AI-based learning motivation can be generalized more broadly. Further studies also need to explore motivational dynamics in greater depth, for example through longitudinal designs or experimental approaches, to understand how students' internal drives develop and influence the use of AI in learning. In addition, learning strategies that integrate the strengthening of technical competencies with the development of autonomous motivation need to be further tested so that the benefits of using AI in an educational context can be optimized.

CONCLUSION AND RECOMMENDATIONS

This study shows that AI Literacy, AI Ethical Awareness, and Motivation to Learn with AI are positively related to Learning Gains, while also providing a stronger theoretical contribution to the fields of AIED, AI literacy theory, and Self-Determination Theory. Findings regarding literacy and ethics confirm that analytical capacity and normative orientation are important foundations for the safe and reflective use of technology. Meanwhile, the dominance of motivation confirms the SDT framework that autonomous motivation acts as a core psychological mechanism that translates cognitive abilities into active engagement in AI-based learning. Thus, this study not only identifies significant predictors of Learning Gains but also emphasizes the importance of integrating cognitive, ethical, and affective factors into a unified framework in AIED design.

Interpretation of these findings still needs to take into account methodological limitations that directly affect the strength of generalization and depth of modeling. The use of a sample from a single institution limits representativeness, while the adaptation of motivational instruments that do not cover the entire spectrum of motivational regulation has the potential to minimize actual psychological variation. The cross-sectional design also does not allow for tracing changes in literacy, ethics, and motivation dynamics over time. Further research is recommended to use a longitudinal design to capture the development of competence and motivation, as well as to apply multidimensional analysis, especially for variables that have a multidimensional structure, such as AI-based learning motivation. This approach will provide a more accurate mapping of constructs, enable more precise effect estimates, and strengthen theoretical and practical contributions to the development of AIED.

REFERENCES

Badarudin, B., Parhanuddin, L., Tohri, A., & Suhardi, M. (2024). The effect of artificial intelligence in education on student motivation: A systematic literature review. *Journal for Lesson and Learning Studies, 8*(1), 1–10. https://doi.org/10.23887/jlls.v8i1.91141

Bećirović, S., Polz, E., & Tinkel, I. (2025). Exploring students’ AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learning Environments, 12*(1). https://doi.org/10.1186/s40561-025-00384-3

BPS Sulawesi Selatan. (2025). *Jumlah perguruan tinggi, dosen, dan mahasiswa (negeri dan swasta) di bawah Kementerian Pendidikan Tinggi, Sains, dan Teknologi menurut kabupaten/kota di Provinsi Sulawesi Selatan, 2024*.

Clark, L. A., & Watson, D. (2019). Constructing validity: New developments in creating objective measuring instruments. *Psychological Assessment, 31*(12), 1412–1427. https://doi.org/10.1037/pas0000626

Costello, E., et al. (2025). Artificial intelligence in educational research and scholarship: Seven framings. *Journal of University Teaching and Learning Practice, 22*(4). https://doi.org/10.53761/xs5e3834

Creswell, J. W., & Creswell, J. E. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage Publications.

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Springer. https://doi.org/10.1007/978-1-4899-2271-7

DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications*. Sage Publications.

Freeman, J. (2025). *Student generative AI survey 2025*.

GEM Report Team. (2023). *Global education monitoring report 2023: Technology in education—A tool on whose terms?* UNESCO. https://doi.org/10.54676/UZQV8501

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

E-ISSN: 2964-3171
P-ISSN: 2985-3214

JUPITER Volume 03 Nomor 03 September 2025

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Kasneci, E., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Knekta, E., Runyon, C., & Eddy, S. (2019). One size doesn't fit all: Using factor analysis to gather validity evidence when using surveys in your research. *CBE—Life Sciences Education, 18*(1), rm1. https://doi.org/10.1187/cbe.18-04-0064

Li, J., et al. (2025). Analyzing the network structure of students' motivation to learn AI: A self-determination theory perspective. *NPJ Science of Learning, 10*(1). https://doi.org/10.1038/s41539-025-00339-w

Morin, A. J. S., Arens, A. K., Tran, A., & Caci, H. (2016). Exploring sources of construct-relevant multidimensionality in psychiatric measurement: A tutorial and illustration using the Composite Scale of Morningness. *International Journal of Methods in Psychiatric Research, 25*(4), 277–288. https://doi.org/10.1002/mpr.1485

Putnick, D. L., & Bornstein, M. H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review, 41*, 71–90. https://doi.org/10.1016/j.dr.2016.06.004

Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research, 47*(5), 667–696. https://doi.org/10.1080/00273171.2012.715555

Rodriguez, A., Reise, S. P., & Haviland, M. G. (2016). Evaluating bifactor models: Calculating and interpreting statistical indices. *Psychological Methods, 21*(2), 137–150. https://doi.org/10.1037/met0000045

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *Journal of Educational Research, 99*(6), 323–338. https://doi.org/10.3200/JOER.99.6.323-338

Sutabri, T., Suroyo, H., & Kurniawan. (2025). Navigating the generative AI revolution in education: A systematic review of applications and ethical considerations. *Jurnal Nasional Pendidikan Teknik Informatika (JANAPATI), 14*(2). https://doi.org/10.23887/janapati.v14i2.90367

Tadesse, T., Gillies, R. M., & Campbell, C. (2018). Testing models and measurement invariance of the learning gains scale. *Education Sciences, 8*(4), 192. https://doi.org/10.3390/educsci8040192

Vansteenkiste, M., Ryan, R. M., & Soenens, B. (2020). Basic psychological need theory: Advancements, critical themes, and future directions. *Motivation and Emotion, 44*(1), 1–31. https://doi.org/10.1007/s11031-019-09818-1

Wadmany, R., & Davidovitch, N. (2025). Students' ethical perceptions of artificial intelligence use: An opportunity for developing a personal ethical compass. *International Journal of Educational Studies, 8*(4), 75–85. https://doi.org/10.53935/2641533x.v8i4.440

Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology, 42*(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Wang, Z., Chai, C. S., Li, J., & Lee, V. W. Y. (2025). Assessment of AI ethical reflection: The development and validation of the AI ethical reflection scale (AIERS) for university students. *International Journal of Educational Technology in Higher Education, 22*(1). https://doi.org/10.1186/s41239-025-00519-z

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist, 34*(6), 806–838. https://doi.org/10.1177/0011000006288127

Zhai, Y., & Nezakatgoo, B. (2025). Evaluating AI-powered applications for enhancing undergraduate students' metacognitive strategies, self-determined motivation, and social learning in English language education. *Scientific Reports, 15*(1), 35199. https://doi.org/10.1038/s41598-025-19118-z