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AI Awareness, Literacy, and Social Influence Predict Ethical Reasoning and Responsible Use in Higher Education

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ABSTRACT

Purpose – This study investigates how AI awareness, AI literacy, and social influence shape students' AI ethics and, consequently, responsible AI use in higher education.

Design/methods/approach – A quantitative cross-sectional survey was conducted with 101 university students in South Sulawesi, Indonesia, who had experience using AI-based learning tools. Data were analyzed using partial least squares structural equation modeling to assess measurement validity and test structural relationships, including the mediating role of AI ethics.

Findings – AI awareness and AI literacy have significant positive effects on AI ethics, with AI literacy emerging as the strongest predictor. Social influence shows a significant negative association with AI ethics, indicating that unregulated peer and environmental pressure may encourage AI adoption while weakening ethical sensitivity. AI ethics significantly predicts responsible AI use and mediates the effects of AI awareness, AI literacy, and social influence on responsible use. These results highlight that responsible AI engagement depends not only on cognitive readiness but also on the ethical norms governing how AI is used in academic contexts.

Research implications/limitations – The study is limited by its cross-sectional design, self-reported data, and a sample restricted to one region, which may limit causal inference and generalizability.

Originality/value – This study provides empirical evidence that AI ethics is a central mechanism linking cognitive and social factors to responsible AI use, informing institutional AI governance, literacy programs, and ethical policy development in higher education.

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INTRODUCTION

Artificial Intelligence in Education (AIED) has grown rapidly and become one of the most influential technological innovations in the transformation of global higher education. The integration of artificial intelligence (AI) in the learning process offers various strategic opportunities, ranging from personalized learning and increased administrative efficiency to strengthening the quality of the student learning experience through the use of automatic writing systems, generative AI platforms, learning recommendation engines, and machine-based assessment systems (Hwang et al., 2020; Matos et al., 2025). This development has not only changed the way students learn but also transformed the role of lecturers, curriculum, and the academic ecosystem as a whole. Various studies have shown that the use of AI in higher education enables data-driven adaptive learning, where the system can adjust the material, pace, and form of feedback according to the individual needs of students (Chen et al., 2020; Crompton & Burke, 2023). AI technology also contributes to faster and more consistent feedback, improved learning accessibility, and support for student-centered learning approaches. In this context, AI is seen as an important catalyst for improving the quality of learning in the 21st century(Li et al., 2024).

As human interaction with machines in learning environments increases, the use of AI in higher education presents complex social, moral, and ethical challenges, requiring students and educators to have not only technical competence but also social and moral understanding to use AI responsibly (Al-Abdullatif, 2025; Li et al., 2024). Without a strong ethical foundation, the use of AI has the potential to cause various problems, such as algorithmic bias, unfairness in assessment, misuse of personal data, privacy violations, excessive dependence on automated systems that weaken students' critical thinking skills, and threats to academic integrity, especially when generative AI is used without a clear understanding of its ethical limitations (Kasneci et al., 2023). Thus, AI awareness and literacy are important foundations for shaping students critical, reflective, and responsible attitudes toward the ethical and meaningful use of AI technology in higher education environments (Kamali et al., 2024; Li et al., 2024; Ng et al., 2021).

AI awareness helps students recognize the potential, benefits, and risks inherent in the use of AI technology in an academic environment. This awareness includes understanding the role of AI in learning, its impact on cognitive processes, and the social and ethical consequences of its use. AI literacy enables students to critically evaluate content generated by AI systems, understand how algorithms work, and assess the moral and social implications of decisions made by this technology (Kamali et al., 2024). AI literacy is not only about technical skills but also includes understanding the limitations of AI systems, potential data bias, and issues of fairness, transparency, and accountability in AI-supported learning processes(Ng et al., 2021). Understanding the mechanisms and limitations of AI is an important prerequisite for students to not passively accept AI outputs, but rather to be able to critically evaluate their accuracy, relevance, and suitability for use in an academic context(Kong et al., 2024; Laupichler et al., 2022)

Students with a higher level of AI awareness tended to be more alert to potential algorithmic bias, limitations in training data, and errors in inference that may arise in AI system outputs. Thus, they do not accept AI results at face value but engage in a process of critical reflection before using them in academic decision-making(Shin, 2021; Williamson et al., 2023). Adequate AI awareness and literacy also encourage students to be more careful in determining the limits of AI use so that it remains in line with academic ethical principles. Previous research has shown that AI awareness and literacy significantly influence student engagement, decision-making, and ethical behavior when interacting with AI tools(Matos et al., 2025). Students with higher levels of AI literacy tend to demonstrate better reflective abilities in determining when, how, and for what purpose AI is used in academic activities(Cotton et al., 2023; Crompton & Burke, 2023). In the context of higher education, AI literacy is also closely related to students' ability to maintain academic integrity, particularly in distinguishing between the use of AI as a learning support tool and practices that could potentially violate academic ethics(Elkhatat et al., 2023; Knell & Rüther, 2023). However, various studies have also revealed that students understanding of AI ethics is still relatively limited, especially in developing countries such as Indonesia. This situation highlights the gap between the level of AI technology adoption and the ethical readiness of its users, thereby emphasising the need for more in-depth and contextual empirical studies (Aswan, 2025; Holmes & others, 2022; Khosibah et al., 2025; Rosyanto et al., 2025)

Although the adoption of AI in Indonesian higher education continues to increase, empirical research comprehensively examining the relationship between AI awareness, AI literacy, social influence, AI ethics, and responsible AI use remains relatively limited. Existing research generally focuses on the technical or pedagogical aspects of AI, while studies that integrate cognitive, social, and ethical dimensions are limited (Kamali et al., 2024). Furthermore, students awareness and perception of AI in the context of higher education have not been explored empirically(Wang et al., 2024). This gap highlights the need for structured research that can explain how these variables interact and collectively influence ethical decision-making in AIED. An integrative approach is essential to understanding the complex dynamics between individual factors, social environment, and ethical values in shaping responsible AI usage behaviour(Creswell & Creswell, 2018; Holmes & others, 2022; Rosyanto et al., 2025)

To address this gap, this study developed a conceptual model that integrates AI awareness, AI literacy, and social influence as predictors of AI ethics and evaluated the contribution of AI ethics to responsible AI use. Using the Partial Least Squares structural equation modelling (PLS-SEM) approach, this study examines the structural relationships between constructs, the validity and reliability of instruments, and the mediating role of AI ethics in explaining AI usage behavior among higher education students (Hair, 2022). This study aims to make a theoretical contribution by clarifying the pathways through which AI awareness, AI literacy, and the social environment shape ethical judgment in the use of AI. In practical terms, the findings of this study are expected to form the basis for developing institutional guidelines, strengthening AI literacy programs, and formulating ethical policies that support the safe, sustainable, and responsible implementation of AIED in higher education. Based on the previously discussed background and conceptual framework, this study formulates the following research questions:

1. Does AI awareness influence the ethical use of artificial intelligence in educational contexts?
2. Does AI literacy influence the ethical use of artificial intelligence in educational contexts?
3. Does social influence affect the ethics of using artificial intelligence in educational contexts?
4. Does the ethics of using artificial intelligence influence the ethical and responsible use of AI in educational contexts
5. Do AI awareness, AI literacy, and social influence collectively affect the ethical and responsible use of AI in educational contexts?

METHOD

Research Design

This study adopts a quantitative approach involving the systematic collection and analysis of numerical data to objectively measure variables, test hypotheses, and generate generalizable findings(Creswell, 2019; Creswell & Creswell, 2018). A cross-sectional survey design was employed, with data collected to capture students ethical awareness and AI literacy in the use of AIED (J. F. Hair et al., 2024; Ringle et al., 2020). This design is appropriate for examining the complex interplay of cognitive, social, and ethical factors influencing responsible AI use without direct intervention, thereby providing a methodological foundation for sampling, instrument development, and data analysis (Hwang et al., 2020).

Participant

The participants in this study consisted of 101 active students from various study programs at universities in South Sulawesi who had used AI-based learning systems, such as ChatGPT, Gemini, Copilot, or similar platforms in academic activities. Students were selected because they represent the group with the highest level of digital interaction and acceptance, making them a relevant group for examining the use of Artificial Intelligence in Education (AIED) (Khosibah et al., 2025; Li et al., 2024). These participant characteristics are considered representative of the relationship between AI awareness, AI literacy, social influence, and the ethics of AIED use in the digital era.

Population and the Methods of Sampling

The study population consisted of active university students in South Sulawesi who had experience using AIED in an academic context. The sampling technique used was purposive sampling, as the study required respondents with specific characteristics, namely, active students who had real experience using AIED(Nurhayati et al., 2024). The inclusion criteria were as follows: (1) active students, (2) involvement in formal and/or non-formal learning, (3) prior use of AIED, and (4) willingness to complete the questionnaire voluntarily. The sample size was determined according to the minimum requirements for Partial Least Squares structural equation modeling (PLS-SEM), which recommends an ideal sample size of at least ten times the number of the most complex structural paths in the model (Kaya & Bayram, 2025). Accordingly, a total of 100 respondents was considered sufficient to meet the minimum standards for PLS-SEM model estimation and provide adequate statistical power (Jang, 2024).

Instrument

The research instrument comprised two sections: a demographic section capturing respondents identity, academic background, region of origin, digital device ownership, and weekly frequency of AI use, and a statement section measuring five variables–AI awareness, AI literacy, social influence, AI ethics, and AI use–using a 1–5 Likert scale (Al-Abdullatif, 2025 ; Puriwat & Tripopsakul, 2021). Data were collected using Google Forms to facilitate efficient questionnaire distribution across universities in South Sulawesi. Details regarding the items, dimensions, and sources of adaptation of this instrument are presented in Table 1 of the following Research Instrument.

Table 1. Research Instruments

No	Variabel	Statement	Reference
1	AI Awareness (AA)	1-5	(Carolus et al., 2023)
2	AI Literacy (AL)	6-10	(Falebita & Kok, 2025)
3	Social Influence (SI)	11-1	(Pallant, 2020)
4	AI Ethics (AE)	16-2	(Al-Abdullatif, 2025; J. F. Jr. Hair et al., 2021)
5	Use of AI (UOA)	21-2	(J. F. Hair et al., 2019)

Source: Processed data, 2025

Procedure

This research was conducted through sequential and systematic stages to ensure data validity, beginning with a literature review and the development of a theoretical framework on AIED, AI literacy, and the moral and social dimensions of its use(Ringle et al., 2020; Al-Abdullatif, 2025; Rosyanto et al., 2025). The next stage included the development and validation of an instrument based on theoretical indicators and empirical findings related to literacy and the ethics of AI use in education(Holmes & others, 2022; Li et al., 2024). After the instrument was declared feasible, a questionnaire was distributed online via Google Forms to efficiently reach students from various universities in South Sulawesi (Nurhayati et al., 2024). This entire series forms a strong methodological basis for examining students emotional attachment to AIED. The stages of the research procedure, from problem formulation to conclusion drawing, are shown in Figure 1.

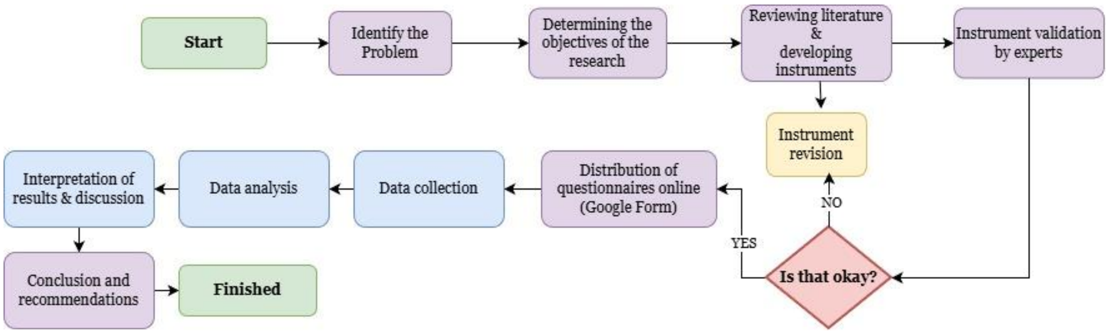

Figure 1. Research Procedure

Data Analysis

Data analysis in this study was conducted in two stages: descriptive and inferential (Ali et al., 2025). The descriptive analysis summarized the respondents characteristics, including gender, age, study program, semester, and frequency of AI use in academic activities, using basic statistics such as percentages, means, medians, and minimum–maximum values, providing an initial overview of the respondent profiles and data patterns. Descriptive statistics were generated using Jamovi because of its user-friendly interface. Inferential analysis was performed using PLS-SEM with SmartPLS software, selected for its suitability for predictive research, complex models, relatively small sample sizes, and data that do not fully meet the normality assumption(López Costa, 2025).

PLS-SEM analysis involved the outer and inner model evaluations. The outer model assessed reliability and validity using outer loadings (≥ 0.708), Cronbach's alpha (≥ 0.70), composite reliability (≥ 0.70), and Rho_A (López Costa 2025). Convergent validity was evaluated using AVE (≥ 0.50) (Kaya & Bayram, 2025), while discriminant validity was examined through the Fornell–Larcker criterion and HTMT, with thresholds of 0.90 (conservative) or 0.85 (liberal). The inner model was evaluated using bootstrapping with 5,000 resamples at $\alpha = 0.05$ and a t-statistic of > 1.96 (Hair Jr et al., 2021). Path coefficients indicate relationship direction and strength, while R^2 and f^2 assess predictive power and effect size. The model comprised five latent variables: AI Awareness, AI Literacy, Social Influence, AI Ethics, and Use of AI, as shown in Figure 2.

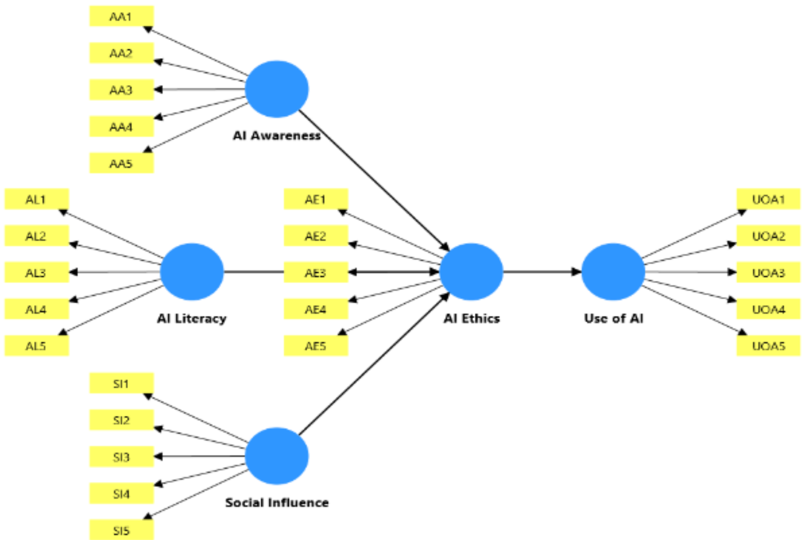

Figure 2. Research Model

Hypothesis:

H_1: AI Awareness has a positive influence on AI Ethics in the educational context.
H_2: AI Literacy has a positive influence on AI Ethics in the educational context.
H_3: Social Influence has a positive influence on AI Ethics in the educational context.
H_4: AI Ethics positively influences the ethical and responsible use of AI in an educational context.
H_{5a}: AI Ethics have a mediating role in the influence of AI Awareness on the ethical and responsible use of AI in the educational context.

H $_{5b}$: AI Ethics has a mediating role in the influence of AI Literacy on the ethical and responsible use of AI in an educational context.
H $_{5c}$: AI Ethics has a mediating role in the influence

RESULTS AND DISCUSSION

Respondent Demographic Analysis

The demographic characteristics of the respondents are presented to provide an overview of the study's sample. A total of 101 respondents participated in this study, and their demographic information is summarized in Table 2, including gender, age, semester, year of study, major, and frequency of technology use in the learning process.

Table 2. Respondent Demographic Data

No.	Category	Description	Percentage (%)
1.	Gender	Man	48.5%
		Woman	51.5%
2.	Age	17 years	4%
		18 years	21.8%
		19 years old	39.6%
		20 years	29.7%
		21 years	4%
		22 years	1.0%
3.	Semester	I	32.7%
		III	56.4%
		V	9.9%
		VII	1.0%
4.	Class Year	2022	1.0%
		2023	9.9%
		2024	56.4%
		2025	32.7%
6.	Major	STEM	76.2%
		Non-STEM	23.8%
7.	Frequency of use of Technology for Learning.	Every day	78.2%
		3-5 Times a Week	17.8%
		1-2 Times a Week	4.0%

Source: Processed data, 2025

Based on Table 2, the distribution of respondents shows gender balance between men (48.5%) and women (51.5%), and domination 18–20 years old, which reflects the characteristics of general student education high. Most participants were from semester III (56.4%) and semester I (32.7%), and the classes of 2024 and 2025 were dominant. Composition This show that respondents especially is students at the stage beginning active study in the lecture process. From the side of academics, a large number of respondents were STEM majors (76.2%), which is relevant to the context of technology-based studies. In addition, the intensity use technology for learning was classified as high, with 78.2% of students using it every day. In overall profile This describe group student young with background STEM background and level utilization powerful technology , though concentration on majors and classes certain need considered as limitation in generalization findings. The evaluation of the Outer model is done to ensure that every latent construct in the PLS-SEM model has adequate validity and reliability.

Measurement Model (Outer Model)

The measurement model was evaluated using the PLS-SEM approach to assess the convergent validity and reliability of the constructs. This evaluation examined indicator loadings, internal consistency reliability, and convergent validity in accordance with established SEM guidelines. Table 3 presents the results of the convergent validity and reliability assessment for all latent constructs in the model: AI Awareness (AA), AI Literacy (AL), Social Influence (SI), AI Ethics (AE), and Use of AI (UOA).

Table 3. Evaluation Results Validity Convergence and Reliability of Constructs

Construct	Item	Outer Loadings	Cronbach's Alpha	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Awareness	AA1	0.845	0.874	0.895	0.908	0.665
	AA2	0.832				
	AA3	0.799				
	AA4	0.880				
	AA5	0.713				
AI Literacy	AL1	0.890	0.894	0.898	0.922	0.704
	AL2	0.897				
	AL3	0.812				
	AL4	0.836				
	AL5	0.751				
Social Influence	AE1	0.859	0.910	0.975	0.930	0.727
	AE2	0.805				
	AE3	0.862				
	AE4	0.891				
	AE5	0.844				
AI Ethics	SI1	0.884	0.918	0.921	0.938	0.753
	SI2	0.810				
	SI3	0.882				
	SI4	0.875				
	SI5	0.885				
Use of AI	UOA1	0.715	0.881	0.886	0.914	0.682
	UOA2	0.850				
	UOA3	0.794				
	UOA4	0.870				
	UOA5	0.887				

Source: Processed data, 2025

The results in Table 3 show that all constructs in the PLS-SEM model met the criteria for convergent validity and reliability. The AI Awareness (AA) construct had outer loadings of 0.713–0.880, Cronbach's Alpha of 0.874, Rho_A of 0.895, CR of 0.908, and AVE of 0.665, confirming that this construct was valid and reliable. The AI Literacy (AL) construct also met the criteria with outer loadings of 0.751–0.897, Cronbach's Alpha of 0.894, Rho_A of 0.898, CR of 0.922, and AVE of 0.704. Furthermore, the Social Influence (SI) construct showed very strong results, with outer loadings of 0.805–0.891, Cronbach's alpha of 0.910, Rho_A of 0.975, CR of 0.930, and AVE of 0.727. The AI Ethics (AE) construct was also reliable and valid, with outer loadings of 0.810–0.885, Cronbach's Alpha of 0.918, Rho_A of 0.921, CR of 0.938, and AVE of 0.753. Meanwhile, the Use of AI (UOA) construct recorded outer loadings of 0.715–0.887, Cronbach's Alpha of 0.881, Rho_A of 0.886, CR of 0.914, and AVE of 0.682, all of which were above the minimum limits.

Validity and reliability testing are crucial for ensuring that the measurement instrument accurately and consistently captures the research constructs. Validity ensures that each indicator truly represents the construct being measured, whereas reliability ensures consistency of responses across participants and situations. By meeting the thresholds for outer loadings, Cronbach's Alpha, Composite Reliability, and AVE, the instrument used in this study was declared robust and reliable, providing a solid basis for interpreting the research findings. Overall, all constructs met the validity and reliability standards recommended in the literature. According to Casal-Otero et al (2023), outer loading values above 0.70, Cronbach's Alpha and Composite Reliability above 0.70, and AVE above 0.50 indicate acceptable levels of reliability and convergent validity in Structural Equation Modeling analysis.

This section also reviews the construct quality aspect through discriminant validity testing to ensure that each variable in the model can be clearly distinguished from one another. Table 4 presents the results of discriminant validity testing using the Fornell–Larcker criterion on a PLS-SEM model involving five latent constructs: AI Awareness (AA), AI Literacy (AL), Social Influence (SI), AI Ethics

(AE), and Use of AI (UOA). In the table, the square root of the Average Variance Extracted (AVE) value of each construct is compared with its correlation with other constructs. The analysis results show that discriminant validity was met, where each construct had a square root of the AVE value that was higher than its correlation with other constructs. This finding indicates that each construct has a good discriminatory ability; therefore, they can be empirically distinguished from one another in the research model. The full details of the test results are presented in Table 4 according to the Fornell–Larcker Criteria*.*

Table 4. Results of the Fornell-Lacker Criterion Validity Test

	AI Awareness	AI Ethics	AI Literacy	Social Influence	Use of AI
AI Awareness	0.816				
AI Ethics	0.718	0.868			
AI Literacy	0.816	0.780	0.839		
Social Influence	0.633	0.419	0.669	0.853	
Use of AI	0.677	0.541	0.734	0.720	0.826

Source: Processed data, 2025

The results of the discriminant validity test using the Fornell–Larcker criterion indicate that all constructs in the model meet good discriminant validity. Each construct, namely, AI Awareness(AA), AI Literacy (AL), Social Influence (SI), AI Ethics (AE), and Use of AI (UOA), had a root A VE value that was higher than its correlation with other constructs. AI Awareness has a root A VE of 0.816, which is higher than all its correlations. AI Ethics has a root AVE of 0.868, which is greater than its correlation with other constructs. AI Literacy recorded a root AVE of 0.839, Social Influence 0.853, and Use of AI 0.826, all of which exceeded their respective correlation values with other constructs. This confirmed that each construct could be clearly distinguished and did not overlap.

Overall, these results confirm that the model meets the requirements for discriminant validity in PLS-SEM, ensuring that each construct accurately measures a distinct aspect of the proposed research framework. This strong discriminant validity provides a solid foundation for proceeding to the next stage of the analysis, namely, evaluating the structural model to examine the relationships between latent constructs through path coefficients in greater depth.

Structural Model (Inner Model)

The structural (inner) model was evaluated to examine the hypothesized relationships among the latent variables using PLS-SEM. This evaluation focused on the significance, direction, and strength of the structural paths based on path coefficients, t-statistics, and p-values obtained through bootstrapping(Ali et al., 2025). Table 5 presents the results of the hypothesis testing and the corresponding decisions regarding each proposed relationship

Table 5. Results of Testing the Relationship between Latent Constructs

Hypothesis	Path Coef	T statistics	P values	Decision
H1 AA -> AE	0.308	2,532	0.006	Positive and Significant
H2 AE -> UOA	0.541	6,707	0.000	Positive and Significant
H3 AL -> AE	0.685	5,666	0.000	Positive and Significant
H4 SI -> AE	-0.234	3.278	0.001	Positive and Significant
H5a AA -> AE -> UOA	0.167	2.435	0.007	Positive and Significant
H5b AL -> AE -> UOA	0.371	3.732	0.000	Positive and Significant

H5c SI-> AE -> UOA	-0.126	3.032	0.001	Positive and Significant

Source: Processed data, 2025

Discussion

The results of the hypothesis testing in Table 5 show that all relationships in the PLS-SEM model are statistically significant, so that each variable in the model makes a significant contribution to the formation of ethics and the use of AI in academic environments. The path coefficient values, t-statistics, and p-values for all constructs confirm that AI Awareness (AA), AI Literacy (AL), and Social Influence (SI) play important roles in shaping AI Ethics (AE), whereas AE has a direct influence on Use of AI (UOA). In addition, the mediation test confirmed that AE is the main pathway connecting AA, AL, and SI to the use of AI by students. Overall, the findings in Table 5 show that the structural model used works well, is consistent, and is supported by strong statistical significance, thus strengthening the relevance of the theoretical relationships formulated in the structural model of this study.

AA positively and significantly influences AE ($\beta = 0.308$, $T = 2.532$, $p = 0.006$). Students who are aware of AI's existence, functions, opportunities, and potential risks tend to have a stronger ethical understanding. This aligns with prior research (Al-Abdullatif, 2025), indicating that awareness is a foundation for moral attitude formation in digital technology use. Awareness enables students to make ethical decisions when using AI in academic learning. AE has a strong positive effect on UOA ($\beta = 0.541$, $T = 6.707$, $p < 0.001$), demonstrating that higher ethical understanding leads to more responsible, safe, and appropriate AI use in academic contexts.

AL exerts the most dominant positive influence on AE ($\beta = 0.685$, $T = 5.666$, $p < 0.001$). Understanding algorithms, data bias, predictive logic, and AI mechanisms allows students to accurately evaluate ethical implications. Sloane and Zakrzewski (2022) confirm that AI literacy enhances both technical skills and moral reasoning, making it a critical factor in ethical AI use.

SI has a significant but negative effect on AE ($\beta = -0.234$, $T = 3.278$, $p = 0.001$). This indicates that strong social pressure from peers, the academic environment, digital communities, or the media can reduce ethical awareness despite promoting AI adoption. Consistent with Chan 2023) and Wiese et al. (2025), social norms can accelerate technology use without enhancing moral sensitivity. Conversely, other studies (Zhai et al., 2021) suggest that social influence can enhance ethical behavior if guided by clear norms. Thus, negative SI in AE highlights the need for academic guidelines and interventions to ensure ethical AI adoption in healthcare. AE positively mediated the relationship between AA and UOA ($\beta = 0.167$, $T = 2.435$, $p = 0.007$). Students awareness of AI risks and benefits fosters ethical understanding, which subsequently encourages responsible and appropriate AI use. This aligns with Sari et al. (2025), who emphasized awareness as a key foundation for digital ethics.

AE significantly mediated the influence of AL on UOA ($\beta = 0.371$, $T = 3.732$, $p < 0.001$). High AI literacy strengthens ethical judgment, leading to safer, more precise, and contextually appropriate AI use in learning, consistent with prior research (Ng et al., 2021).

AE negatively mediated the relationship between SI and UOA ($\beta = -0.126$, $T = 3.032$, $p = 0.001$). This confirms that unregulated social pressure can reduce the quality of AI usage. Students influenced by peer pressure without ethical guidance may adopt AI inappropriately, for example, for plagiarism or content manipulation. This supports Hwang et al.(2020), whohhighlighteds that social dynamics can promote technology adoption but not necessarily ethical awareness. Educational interventions are needed to ensure ethical considerations, despite social pressures. Awareness, AI Literacy, and Social Influence significantly shape AI Ethics, which is the primary determinant of responsible AI use. Individual factors (AA, AL) should be strengthened through curriculum and literacy programs, while social factors (SI) require clear ethical guidelines and pedagogical support. STEM students tend to exhibit higher AI literacy and awareness owing to their intensive exposure to digital technologies, computational problem-solving, and laboratory practices(Long & Magerko, 2020; Leon et al., 2025). Technology-rich learning environments further enhance ethical awareness, bias recognition and responsible AI use (Sari et al., 2025).

The findings of this study have important implications for higher education and AI integration practices. The results underscore the pivotal role of AI Ethics as a central mechanism linking AI awareness, AI literacy, and social influence to responsible AI use. This suggests that educational institutions should move beyond merely promoting AI adoption and emphasize ethical reasoning and critical evaluation in AI-related learning. Integrating AI ethics into curricula, providing clear institutional guidelines, and embedding ethical considerations into assessment practices may help ensure that AI technologies are used responsibly and contextually in academic settings. In addition to these practical implications, this study contributes to the existing body of knowledge by empirically demonstrating the mediating role of AI Ethics within a comprehensive PLS-SEM framework. By simultaneously examining cognitive (AI awareness and literacy) and social factors (social influence), this study extends prior AI adoption studies that often overlook ethical dimensions. Moreover, by providing empirical evidence from a higher education context in South Sulawesi, this study enriches the literature with insights from a developing region, which remains underrepresented in AI ethics and education research.

Despite these contributions, this study has several limitations. The cross-sectional research design restricts the ability to draw causal inferences regarding the relationships between the constructs. Additionally, reliance on self-reported data may introduce response bias, as participants might overestimate their ethical awareness or responsible AI use. The sample, which was limited to university students in South Sulawesi, may also constrain the generalizability of the findings to other regions, disciplines and educational systems. Building on these limitations, future research should adopt longitudinal or mixed-methods approaches to capture changes in AI ethics and usage behavior over time. Further studies should explore disciplinary differences more explicitly, particularly between STEM and non-STEM students, to better understand contextual variations in AI literacy and ethical reasoning. Expanding the model to include moderating variables such as institutional policies, cultural values, and instructional strategies may provide deeper insights into how ethical AI use can be effectively fostered in diverse educational settings.

CONCLUSION

This study confirms that AI ethics is the key pathway through which cognitive readiness and social dynamics shape responsible AI use in higher education. AI awareness and AI literacy strengthen ethical reasoning, with AI literacy emerging as the strongest predictor of AI ethics. In contrast, social influence negatively affects AI ethics, suggesting that peer-driven norms can accelerate AI adoption without sufficient ethical reflection. These findings imply that responsible AI use cannot be achieved through access and adoption efforts alone. Universities should combine structured AI literacy development with explicit ethics education, clear institutional guidelines, and assessment practices that reinforce academically appropriate AI use. Given the cross-sectional design, reliance on self-reported measures, and regional sampling, future studies should employ longitudinal or mixed-method approaches, compare STEM and non-STEM cohorts, and test additional contextual moderators such as institutional policy clarity and academic integrity climate.

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AUTHOR CONTRIBUTION STATEMENT

NF conceptualized the study, developed the research framework, and drafted the manuscript. AD, DF contributed to instrument development, data collection, and preliminary data processing. AN and MMF performed the statistical analysis using partial least squares structural equation modeling and supported interpretation of results. All authors reviewed, revised, and approved the final manuscript and agreed to be accountable for all aspects of the work.

AI DISCLOSURE STATEMENT

The authors declare that generative AI tools were used solely to support language editing, clarity, and readability during manuscript preparation. AI tools were not used to generate research ideas, design the study, collect data, conduct statistical analysis, interpret results, or draw conclusions. All

AI-assisted text was reviewed and edited by the authors, who take full responsibility for the accuracy, originality, and integrity of the manuscript.

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