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Original Research

Investigating the Relationship between AI Literacy and Ethical AI Use among Cambodian Undergraduate Students: The Mediating Role of Perceived AI Ethics

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ABSTRACT

With the growing integration of artificial intelligence (AI) into higher education, promoting students' ethical AI use has become an important concern. However, empirical evidence on the relationships among AI literacy, perceived AI ethics, and AI ethical use remains limited, particularly in Cambodia. This study examines the relationships among AI literacy, perceived AI ethics, and AI ethical use, including the mediating role of perceived AI ethics. Using a quantitative correlational design, data were collected from 286 undergraduates at four Cambodian universities through convenience sampling and analyzed with SPSS and SmartPLS. AI literacy positively influenced perceived AI ethics ($\beta = 0.732$, $p < 0.001$) and AI ethical use ($\beta = 0.254$, $p = 0.005$), and perceived AI ethics positively affected AI ethical use ($\beta = 0.571$, $p < 0.001$). Perceived AI ethics also partially mediated the relationship between AI literacy and AI ethical use ($\beta = 0.418$, $p < 0.001$). The model explained 53.6% of the variance in perceived AI ethics and 60.3% in AI ethical use. These findings highlight the need to strengthen AI literacy and ethical perceptions, with implications for policymakers, universities, and educators. Future research should validate the model in other contexts.

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1. INTRODUCTION

Artificial intelligence (AI) has transformed various sectors, including higher education, by changing how operations are conducted and services are delivered, thereby improving efficiency and fostering innovation (Younas et al., 2024). In higher education, AI is reshaping the academic landscape by enabling more personalized, flexible, and efficient learning experiences (Jeilani & Abubakar, 2025). As AI technologies become increasingly prevalent, understanding students' perceptions of AI-supported learning is essential for promoting effective adoption and improving learning outcomes (Jeilani & Abubakar, 2025). AI-supported learning refers to the integration of AI technologies into educational activities to enhance teaching and learning experiences (Younas et al., 2024). Previous studies across different higher education contexts have shown that AI integration can improve students' learning experiences by providing adaptive learning systems, personalized support, and greater access to educational resources. For example, studies conducted in the United States and Malaysia found that AI-supported systems, including adaptive learning platforms and intelligent tutoring technologies, enhanced learning effectiveness and academic support (Rangavittal, 2024; Mat Yusoff et al., 2025).

Similarly, research in Greece and Indonesia highlighted the role of AI in expanding access to global knowledge, supporting language learning, and facilitating research-related tasks (Kalniņa et al., 2024; Younas et al., 2024). Studies conducted in Romania, Ukraine, China, Oman, and Vietnam also reported positive outcomes associated with student motivation, engagement, critical thinking, personalized learning, and independent learning (Vieriu & Petrea, 2025; Davidovitch & Gerkerova, 2026; Slimi et al., 2025; Yan et al., 2025; Tran & Truong, 2026). Collectively, these findings highlight the growing importance of AI in supporting various aspects of student learning in higher education. Despite these benefits, the integration of AI into higher education has raised concerns about students' ethical and responsible use of these technologies. Evidence from Greece, China, Indonesia, and Vietnam suggests that, although AI can support learning, its use may also be associated with challenges involving critical thinking, independent problem-solving, and creativity (Kalniņa et al., 2024; Fernando & Li, 2025; Al-kumaim et al., 2025; Lan & Van, 2025).

Further concerns relate to students' dependence on AI to complete academic tasks, the production of coursework without sufficient critical reflection, and the potential for information overload. These concerns highlight the importance of understanding the factors associated with ethical AI use among university students. Although previous studies have identified AI literacy as an important factor in promoting responsible AI use, the mechanisms underlying this relationship remain insufficiently understood. In particular, limited research has examined whether students' perceptions of AI ethics help explain the relationship between AI literacy and ethical AI use. Furthermore, existing evidence has largely come from countries such as Germany and Indonesia (Sloane & Zakrzewski, 2022; Febrianti et al., 2026), while empirical evidence from Cambodian higher education remains limited.

This study aims to address these gaps through two contributions. Contextually, it provides evidence from Cambodian higher education, where research on students' ethical AI use remains scarce, and findings from elsewhere may not generalize given differences in institutional policies, digital infrastructure, and AI adoption. Methodologically, it moves beyond treating AI literacy as a direct predictor of ethical AI use by testing perceived AI ethics as a mediator, an approach rarely applied in prior work. Partial least squares structural equation modeling (PLS-SEM) is employed because it suits prediction-oriented research and complex models with mediating relationships. This study examines the direct effects of AI literacy on perceived AI ethics and ethical AI use, and of perceived AI ethics on ethical AI use, as well as the indirect effect of AI literacy on ethical AI use through perceived AI ethics among Cambodian undergraduate students. The findings are expected to provide useful insights for policymakers, higher education institutions, and academics seeking to promote ethical AI

2. LITERATURE REVIEW

2.1. AI Integration in Higher Education

Artificial Intelligence (AI) in higher education refers to the integration of AI technologies into teaching, learning, and administrative processes to enhance personalized learning, learning effectiveness, resource allocation, and student engagement (Kuleto et al., 2021). AI applications include personalized learning, adaptive tutoring, real-time feedback, natural language processing, immersive learning, and predictive analytics (Long et al., 2026). A global survey of 3,839 university students across 16 countries found that 86% used AI for academic purposes, particularly for information searching, grammar checking, summarization, paraphrasing, and text generation (Kelly, 2024). AI tools such as ChatGPT, Microsoft Copilot, and Gemini are increasingly used for learning, academic writing, research, and problem-solving (Tick et al., 2023; Yu et al., 2024; Alkaabi et al., 2025; Villaceran & Himang, 2025; Limna & Kraiwanit, 2024; Shaengchart et al., 2025; Kaul & Raghuwanshi, 2026).

Despite these benefits, concerns have emerged regarding students' ethical use of AI. Excessive reliance on AI may reduce critical thinking and independent learning (Arowosegbe et al., 2024; Osang et al., 2025; Khasawneh, 2024; Alnsour et al., 2025; Saxena & Bajotra, 2024), while inappropriate use may compromise academic integrity and encourage irresponsible learning behaviours (Xue et al., 2025; Atma et al., 2026; Hanh & Duyen, 2025). These concerns highlight the need to identify factors that promote and strengthen ethical AI use among university students. Recent studies have identified AI literacy as an important factor in responsible AI use across higher education contexts, including the United Kingdom, Croatia, Slovenia, India, Kazakhstan, Bangladesh, China, Malaysia, and Indonesia (O'Dea et al., 2025; Rožman et al., 2025; Abayeva & Butabayeva, 2026; Anam et al., 2025; Sun et al., 2026; Jamaluddin & Jamaluddin, 2025; Saputra et al., 2026). Students with higher AI literacy are better able to understand AI technologies, critically evaluate AI-generated information, and recognize the ethical implications of AI use. However, the mechanism through which AI literacy contributes to ethical AI use remains insufficiently understood.

In Cambodia, research on AI in higher education has mainly examined students' perceptions, attitudes, adoption, and learning outcomes. Sol et al. (2024) investigated students' experiences and perceptions of AI in English language learning, while Hoeurng et al. (2024) examined AI applications in academic research; Be

(2026) and Huy et al. (2026) explored AI adoption, attitudes, and learning outcomes. Other studies have examined AI literacy, readiness, and AI integration, including students' AI literacy and experiences (Tao et al., 2026), readiness for AI-enhanced learning (Huot & Loch, 2025), and the benefits and challenges of AI adoption (Pum & Sok, 2024). Academic integrity has also received attention through discussions of academic integrity policies (Sok & Heng, 2024). Collectively, these studies show whether Cambodian students use AI and how they perceive it, but they leave three gaps.

First, prior studies concentrate on adoption, perceptions, readiness, and learning outcomes rather than on whether students use AI ethically, so empirical evidence on ethical AI use among Cambodian undergraduates remains limited. Second, the integrity-related work is policy-oriented and offers insufficient empirical evidence on students' own ethical AI behavior. Third, none of these studies test the mechanism through which AI literacy may lead to ethical AI use, in particular whether students' perceived AI ethics explains this association. Without this evidence, universities and policymakers cannot tell whether building AI literacy alone is enough to promote ethical use or whether ethical awareness must be developed explicitly. Thus, this study addresses these gaps by developing and testing a PLS-SEM model of the direct effects of AI literacy on perceived AI ethics and ethical AI use, and of the mediating role of perceived AI ethics. In doing so, it provides Cambodia-specific empirical evidence on the mechanism behind ethical AI use.

2.2. Hypothesis Development

2.2.1. AI Literacy and AI Ethical Use

AI literacy refers to the ability to understand, evaluate, and appropriately use AI technologies while critically considering their implications (Chiu et al., 2024; Pramod, 2025). Higher AI literacy enables students to understand AI capabilities and limitations, critically evaluate AI-generated information, and follow appropriate guidelines for AI use. Previous studies have found that AI-literate students are more capable of applying AI responsibly and ethically in academic settings (Adamoli et al., 2025; Bewersdorff et al., 2025). Therefore, the following hypothesis is proposed:

H1: There is a positive relationship between AI literacy and AI ethical use among undergraduate students.

2.2.2. AI Literacy and Perceived AI Ethics

AI literacy enables students to critically examine AI technologies and recognize their ethical implications, including issues of privacy, fairness, transparency, and accountability (Pramod, 2025; Abayeva & Butabayeva, 2026). Students with higher AI literacy are therefore better equipped to identify and evaluate ethical concerns associated with AI use. Previous research has reported a positive relationship between AI literacy and students' awareness of AI-related ethical issues (Nurhaliza, 2025; Meneses, 2026). Thus, the following hypothesis is proposed:

H2: There is a positive relationship between AI literacy and perceived AI ethics use among undergraduate students.

2.2.3. Perceived AI Ethics and AI Ethical Use

Perceived AI ethics reflects students' recognition and evaluation of ethical principles associated with AI use, including fairness, accountability, transparency, privacy, and academic integrity (Goreta et al., 2024; Ghosh, 2025). Stronger ethical perceptions can guide students in evaluating the risks and appropriateness of AI applications and encourage responsible use consistent with academic standards. Previous studies have found that ethical perceptions are positively associated with responsible and ethical AI use (Kong & Zhu, 2025; Febrianti et al., 2026). Therefore, the following hypothesis is proposed:

H3: There is a positive relationship between perceived AI ethics and AI ethical use among undergraduate students.

2.2.4. Mediating Role of Perceived AI Ethics

Perceived AI ethics may explain how AI literacy translates into ethical AI use (Toker Gökçe et al., 2025). AI literacy equips students with the knowledge and skills to understand AI capabilities, limitations, and ethical implications, thereby strengthening their ethical evaluations of AI use (Abayeva & Butabayeva, 2026). These ethical perceptions may subsequently encourage students to apply AI more responsibly in academic settings (Xie et al., 2025; Pramod, 2025). Thus, perceived AI ethics may serve as a mechanism linking AI literacy with AI ethical use. Accordingly, the following hypothesis is proposed:

H4: There is a significant mediating role of perceived AI ethics in the relationship between AI literacy and AI ethical use among undergraduate students.

2.3. Conceptual Framework

Drawing on previous empirical studies, this research proposes an integrated framework to examine the relationships among AI literacy, perceived AI ethics, and ethical AI use among Cambodian undergraduate students. AI literacy is included because students who understand AI capabilities and limitations are better able to evaluate AI-generated information critically and apply AI appropriately in academic tasks. Additionally, perceived AI ethics is included because students' ethical perceptions, such as their views on academic integrity,

privacy, fairness, and accountability, guide their judgment about what counts as acceptable AI use. These constructs capture two complementary foundations of responsible behavior, including knowing how AI works and understanding how it should be used. Knowledge alone may not ensure responsible use, whereas ethical perceptions are more likely to shape behavior when students understand the technology. Perceived AI ethics is therefore modelled as both a predictor and a mediator, because it helps among these constructs and the mediating role of perceived AI ethics. The proposed relationships will be tested using PLS-SEM, as illustrated in Figure 1.

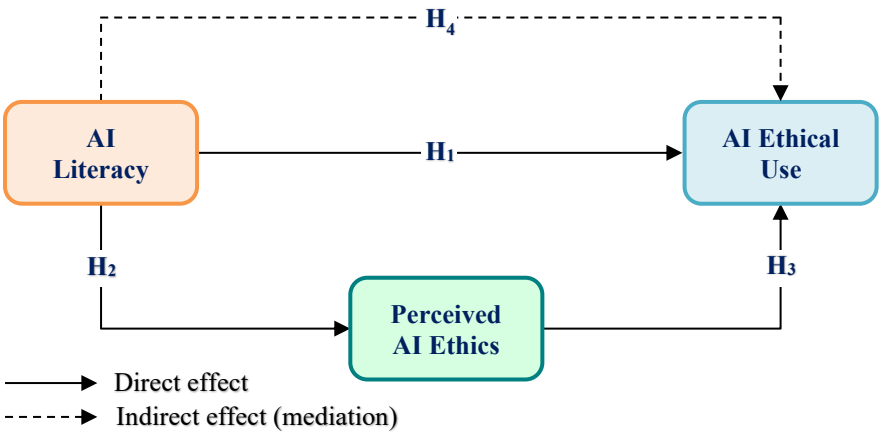


Figure 1. Conceptual Framework

3. METHODS

3.1. Research Design

This study employed a quantitative correlational research design to examine the relationships between the proposed constructs and ethical AI use among Cambodian undergraduate students. The quantitative approach was suitable for systematically measuring variables, statistically evaluating relationships among constructs, and collecting data from a relatively large sample. A survey questionnaire was used to efficiently collect respondents' perceptions and experiences. The correlational design was appropriate for PLS-SEM because the study aimed to examine associations among latent constructs and assess both direct relationships and the mediating role of perceived artificial intelligence ethics without manipulating the study variables. Furthermore, PLS-SEM supported the simultaneous assessment of the proposed relationships and the explanatory power of the research model. Overall, this design was appropriate for addressing the study objectives and testing the proposed hypotheses.

3.2. Sample and Sampling Design

The minimum sample size for this study was determined using G*Power software (Faul et al., 2009). Given that the study employed PLS-SEM to examine the relationships among the study constructs, an a priori power analysis was conducted using a medium effect size ($f^2 = 0.15$), a significance level of 0.05, a statistical power of 0.95, and two predictors. The analysis indicated that the minimum required sample size was 104 respondents. Therefore, the final sample of 286 undergraduate students exceeded the minimum requirement, providing an adequate basis for the planned PLS-SEM analysis and hypothesis testing. The study collected data from undergraduate students at three private universities and one public university in Phnom Penh, Cambodia: BELTEI International University, ACLEDA University of Business, the Institute of Banking Studies, and the National University of Management.

Convenience sampling was employed to recruit students who had experience using AI tools for academic purposes. This eligibility criterion ensured that respondents had relevant experience to evaluate AI literacy, perceived AI ethics, and ethical AI use behavior. The final sample of 286 respondents was retained to support the planned statistical analysis and provide sufficient observations for estimating the relationships among the study constructs. Although the sample exceeded the minimum required by the G*Power analysis, convenience sampling may limit the representativeness of the findings. Accordingly, the results should be

interpreted within the context of the participating higher education institutions in Phnom Penh and should not be generalized to all university students in Cambodia.

3.3. Research Instruments

The questionnaire comprised demographic information and measurement items adapted from prior studies, as presented in Table 1. The items were modified to fit the local context and improve clarity. The questionnaire was translated into Khmer and back-translated into English by two bilingual researchers, with minor revisions made following a pilot test. A bilingual Khmer–English questionnaire was used for data collection. All items were measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) (Koo & Yang, 2025). Mean scores were interpreted as 1.00–1.80 = strongly disagree, 1.81–2.60 = disagree, 2.61–3.40 = neutral, 3.41–4.20 = agree, and 4.21–5.00 = strongly agree (Koo & Yang, 2025).

Table 1. A summary of the construct measurement

Description	Number of items	Sources
AI Literacy	AIL1 – AIL5	Robert et al. (2024); Osasona et al. (2024); Deranty & Corbin (2024)
Perceived AI Ethics	PAIE1 – PAIE5	Chan (2023); Rahiman & Kodikal (2024); Al Shamsi et al. (2025)
AI Ethical Use	AIEU1 – AIEU7	Chan (2023); Febrianti et al. (2026); Promma (2025)

3.4. Data Collection Procedures

Data collection was conducted in two phases among Cambodian university students from three private universities and one public university. First, a pilot test involving 114 undergraduate students at BELTEI International University was conducted from June 9 to June 16, 2026. All pilot participants had prior experience using AI, and their responses were used to assess item clarity and preliminary reliability using Cronbach's alpha. These participants were excluded from the main survey. Minor revisions were made based on the pilot results before the main survey. Second, the main survey was conducted from June 18 to July 21, 2026, involving 286 undergraduate students from four targeted universities. Data were collected through Google Forms distributed via Telegram. Participation was voluntary, with informed consent, confidentiality, and ethical procedures ensured. Institutional approval was obtained from relevant faculty representatives and lecturers before data collection. The final data were analyzed using PLS-SEM to assess the measurement model and test the hypothesized relationships.

3.5. Data Analysis Method

Data were analyzed using Microsoft Excel 2019, IBM SPSS Statistics 27, and SmartPLS 3. Excel was used for data screening, coding, and preparation, while SPSS was used to generate descriptive statistics and assess preliminary reliability. Before the main survey, a pilot test with 114 respondents was conducted to assess item clarity and internal consistency using Cronbach's alpha. A Cronbach's alpha ≥ 0.70 was considered acceptable, and an Average Inter-Item Correlation (AIIC) between 0.30 and 0.70 was also considered acceptable (Gliem & Gliem, 2003; Gharaibeh et al., 2017). The main data were analyzed using PLS-SEM in SmartPLS 3, following the two-stage approach recommended by Hair et al. (2022). First, the measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity.

Indicator reliability was assessed using outer loadings, with values ≥ 0.70 considered desirable. Internal consistency was assessed using Cronbach's alpha, composite reliability (CR), and rho_A (Hair et al., 2022). Convergent validity was evaluated using the average variance extracted (AVE), while discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT), with HTMT values below 0.85 indicating good discriminant validity and values below 0.90 considered acceptable (Fornell & Larcker, 1981; Henseler et al., 2015). Second, the structural model was evaluated using variance inflation factors (VIF), effect size (f^2), path coefficients (β), coefficient of determination (R^2), and predictive relevance (Q^2) (Hair et al., 2022). Hypotheses were tested using bootstrapping to assess the significance of direct and indirect effects based on t-values, p-values, and confidence intervals. The assessment criteria for the measurement and structural models are summarized in Table 2.

Table 2. Evaluation criteria for PLS-SEM analysis

Model Assessment	Criteria	Sources
Outer loading	≥ 0.70	Hair et al. (2022)
α	≥ 0.70	Hair et al. (2022)
CR	≥ 0.70	Hair et al. (2022)
AVE	≥ 0.50	Fornell and Larcker (1981)
HTMT ratio	< 0.85 or < 0.90	Henseler et al. (2015)
VIF	< 5.00	Hair et al. (2022)
β	t-value > 1.96 and p-value < 0.05	Hair et al. (2022)
R^2	0.25 = weak, 0.50 = moderate, and 0.75 = substantial	Hair et al. (2022)
f^2	0.02 = small, 0.15 = medium, and 0.35 = large	Hair et al. (2022)
Q^2	$Q^2 > 0$	Hair et al. (2022)
Bootstrapping	5,000 subsamples	Hair et al. (2022)

4. RESULTS

4.1. Respondent Demographics

Table 3 presents the demographic characteristics of the 286 participants. The sample was predominantly female and largely composed of students aged 18–20 years. Most respondents were from BELTEI International University, followed by ACLEDA University of Business, National University of Management, and the Institute for Banking Studies. Regarding AI training experience, the majority of students reported having no formal AI training, while the remaining participants indicated exposure through online training, offline training, or both forms of training.

Table 3. Demographic characteristics of the respondents

Demographic	Description	Frequency	Percentage (%)
Gender	Male	80	28.0
	Female	206	72.0
Age Group	18–20 years old	183	64.0
	21–23 years old	83	29.0
	24–26 years old	12	4.2
	Above 26 years old	8	2.8
University	BELTEI International University	233	81.5
	ACLEDA University of Business	22	7.7
	Institute for Banking Studies	14	4.9
	National University of Management	17	5.9
AI Training Experience	Yes, online only	57	19.9
	Yes, offline only	45	15.7
	Yes, both online and offline	18	6.3
	No	166	58.0

4.2. Descriptive Statistics

Table 4 shows that respondents agreed with all three constructs, with mean scores ranging from 3.76 to 3.84 on the five-point scale. AI ethical use scored highest (M = 3.84), followed by perceived AI ethics (M = 3.77) and AI literacy (M = 3.76). These results suggest that students generally reported adequate AI literacy, positive perceptions of AI ethics, and a favorable tendency toward ethical AI use. The standard deviations (0.55-0.58) were small, indicating that responses were fairly consistent across respondents.

Table 4. Results of descriptive statistics

No	Constructs	Minimum	Maximum	M	STDEV	Level of Agreement
1	AI Literacy	1.80	5.00	3.757	0.547	Agree
2	Perceived AI Ethics	1.80	5.00	3.772	0.568	Agree
3	AI Ethical Use	1.00	5.00	3.835	0.578	Agree

Note. STDEV = Standard Deviation; M = Mean: 1.00–1.80 = Strongly Disagree; 1.81–2.60 = Disagree; 2.61–3.40 = Neutral; 3.41–4.20 = Agree; and 4.21–5.00 = Strongly Agree

4.3. Reliability Analysis

Table 5 demonstrates that, based on the pilot sample of 114 respondents, the measurement items consistently capture their respective constructs. The results indicate good internal consistency across AI Literacy, Perceived AI Ethics, and AI Ethical Use. The AIIC values also indicate that the items are sufficiently related while remaining distinct, suggesting that the scales provide reliable and non-redundant measures. Overall, the refined items are considered reliable and appropriate for subsequent PLS-SEM analysis. These findings provide empirical justification for retaining the refined items for the main survey and subsequent analysis. The consistency of the reliability results across all three constructs also supports the adequacy of the measurement instrument for collecting data from the main sample.

Table 5. Reliability analysis of measurement items

Code	Item Description	Cronbach's alpha	AIIC
AI Literacy		0.858	0.548
AIL1	I know how to use AI tools effectively while protecting personal and academic data.	0.841	
AIL2	I can identify potential bias or unfairness in AI-generated information.	0.838	
AIL3	I am aware of the ethical risks and limitations associated with using AI for academic tasks.	0.821	
AIL4	I can determine when the use of AI is appropriate or inappropriate in academic work.	0.828	
AIL5	I critically evaluate AI-generated content to ensure it is accurate, reliable, and ethically appropriate before using it.	0.813	
Perceived AI Ethics		0.847	0.531
PAIE1	I understand the importance of protecting personal data when using AI tools.	0.809	
PAIE2	I have a responsibility to use AI technologies appropriately and ethically in academic studies.	0.811	
PAIE3	I critically examine the sources of information provided by AI.	0.832	
PAIE4	I am aware that AI should support students' learning without causing harm.	0.810	
PAIE5	I understand the importance of adhering to ethical guidelines for the use of AI in education.	0.818	
AI Ethical Use		0.916	0.608
AIEU1	I use AI tools to support my learning while maintaining academic integrity.	0.911	
AIEU2	I critically and ethically evaluate information from AI tools before using it.	0.907	
AIEU3	I use AI tools to generate ideas while maintaining my own originality.	0.898	
AIEU4	I use AI tools without relying on them completely.	0.907	
AUEU5	I obey proper guidelines when using AI tools in my academic work.	0.899	
AIEU6	I use AI tools to improve my understanding of course materials while upholding academic integrity.	0.900	
AIEU7	I use AI tools selectively and ethically when they suit my academic needs.	0.898	

Note. Cronbach's alpha: excellent (> 0.90); good (0.80–0.89); acceptable (0.70–0.79); questionable (0.60–0.69); poor (0.50–0.59); and unacceptable (< 0.50); AIIC: $0.30 \leq \text{AIIC} \leq 0.70$.

4.4. Measurement Model Assessment

Table 6 presents the measurement model assessment results. The outer loadings ranged from 0.703 to 0.825, exceeding the recommended threshold of 0.70 and indicating satisfactory indicator reliability. Cronbach's alpha values ranged from 0.799 to 0.881, rho_A values ranged from 0.801 to 0.884, and composite reliability values ranged from 0.861 to 0.908, all exceeding 0.70 and indicating acceptable internal consistency reliability. Furthermore, the average variance extracted values ranged from 0.554 to 0.595, exceeding the recommended minimum of 0.50 and supporting convergent validity. Overall, the results indicate that the measurement model demonstrated satisfactory indicator reliability, internal consistency reliability, and convergent validity, supporting further assessment of the structural model.

Table 6. Measurement model assessment

Constructs	Item	Outer Loading	Cronbach's alpha	rho_A	CR	AVE
AI Literacy	AIL1	0.758	0.799	0.801	0.861	0.554
	AIL2	0.744				
	AIL3	0.78				
	AIL4	0.703				
	AIL5	0.727				
Perceived AI Ethics	PAIE1	0.762	0.829	0.834	0.880	0.595
	PAIE2	0.809				
	PAIE3	0.706				
	PAIE4	0.757				
	PAIE5	0.819				
AI Ethical Use	AIEU1	0.740	0.881	0.884	0.908	0.586
	AIEU2	0.706				
	AIEU3	0.825				
	AIEU4	0.721				
	AIEU5	0.812				
	AIEU6	0.774				
	AIEU7	0.769				

4.5. Discriminant Validity Assessment

Table 7 shows the results of the discriminant validity assessment using the heterotrait–monotrait ratio (HTMT) criterion. The HTMT values among all constructs ranged from 0.798 to 0.888, which were below the recommended threshold of 0.90. The HTMT value between AIL and PAIE was 0.888, while the values between AIL and AIEU and between PAIE and AIEU were 0.798 and 0.881, respectively. These results confirm that all constructs achieved satisfactory discriminant validity, indicating that each construct represents a distinct concept within the measurement model.

Table 7. HTMT criterion

Construct	AI Literacy	Perceived AI Ethics	AI Ethical Use
AI Literacy	—		
Perceived AI Ethics	0.888	—	
AI Ethical Use	0.798	0.881	—

The diagonal values, representing the square roots of the average variance extracted, ranged from 0.744 to 0.776 and exceeded the corresponding inter-construct correlations, which ranged from 0.667 to 0.752. These results support discriminant validity among the three constructs according to the Fornell–Larcker criterion. All inter-construct correlations were statistically significant at the 0.01 level, as shown in Table 8.

Table 8. Fornell–Larcker criterion and correlation matrix

Construct	AI Literacy	Perceived AI Ethics	AI Ethical Use
AI Literacy	**0.744**		
Perceived AI Ethics	0.724	**0.771**	
AI Ethical Use	0.667	0.752	**0.776**

Note: Bold diagonal values represent √AVE; off-diagonal values indicate inter-constructcorrelations; ** Correlation is significant at the 0.01 level (2-tailed)

4.6. Structural Model Assessment

Figure 2 presents the structural model estimated using the PLS algorithm in SmartPLS. The figure illustrates the hypothesized relationships among AIL, PAIE, and AIEU, including the standardized path coefficients (β) and the coefficient of determination (R^2) of the endogenous construct. Following the estimation of the structural model, the model was assessed through collinearity analysis, explanatory power, effect size, predictive relevance, and hypothesis testing. The significance of the hypothesized relationships was evaluated using the bootstrapping procedure, and the results are presented in the following sections.

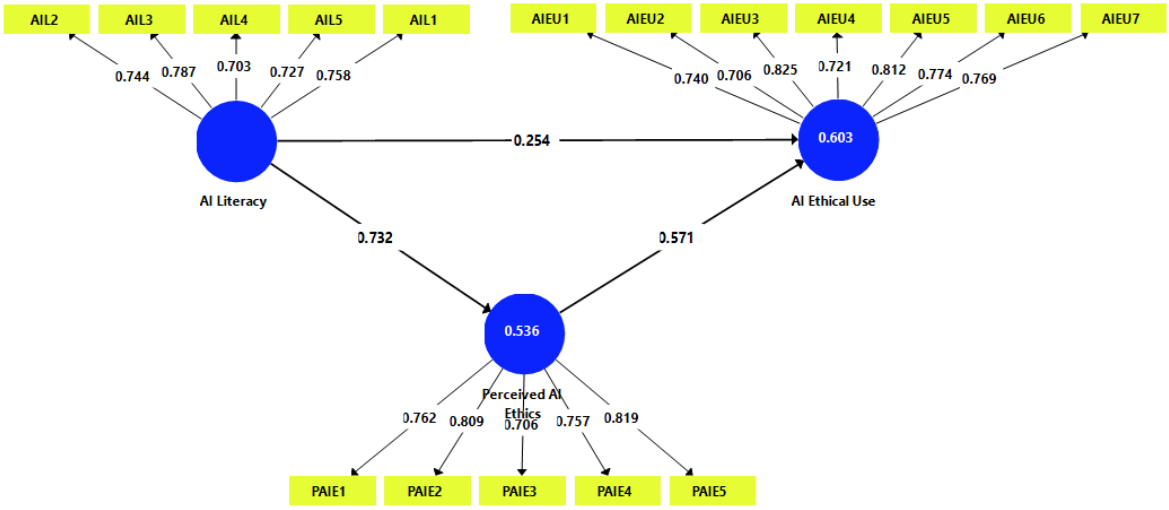


Figure 2. Structural model estimated using the PLS algorithm

4.7. Collinearity Statistics

Collinearity was assessed using inner VIF values. All values were below the recommended threshold of 5.00, indicating no critical collinearity concerns among the predictor constructs in the structural model, as shown in Table 9. The VIF values ranged from 1.00 to 2.157. These results suggest that multicollinearity is unlikely to substantially distort the estimated path coefficients. Therefore, the structural model demonstrates acceptable collinearity levels for evaluating the hypothesized relationships.

Table 9. Results of collinearity statistics

Assessment	Constructs	VIF	Interpretation
Inner VIF	AI Literacy	2.157	No problematic collinearity
Inner VIF	Perceived AI Ethics	2.157	No problematic collinearity
Inner VIF	AI Ethical Use	1.00	No problematic collinearity

4.8. Structural Model Quality Assessment

According to Table 10, the structural model was assessed using R^2, f^2, and Q^2. Perceived AI Ethics showed moderate explanatory power ($R^2 = 0.536$) and predictive relevance ($Q^2 = 0.344$), while AI Ethical Use demonstrated higher explanatory power ($R^2 = 0.603$) and predictive relevance ($Q^2 = 0.311$). The effect sizes ranged from small to large, with the largest effect observed for Perceived AI Ethics on AI Ethical Use ($f^2 = 0.380$). Overall, the results confirm satisfactory explanatory and predictive capability of the structural model.

Table 10. Structural model quality assessment

Endogenous Constructs	R^2	Adjusted R^2	Q^2	Exogenous	f^2	Effect Size
Perceived AI Ethics	0.536	0.535	0.344	AI Literacy	0.075	Small
AI Ethical Use	0.603	0.600	0.311	AI Literacy	0.157	Medium
	–	–	–	Perceived AI Ethics	0.380	Large

4.9. Hypothesis Testing of Direct Effect

Table 11 presents the results of the structural model assessment based on the bootstrapping procedure. A path was considered significant when the t-value exceeded 1.96 and the p-value was below 0.05, so all three hypothesized paths were supported. AI literacy had a significant positive effect on both AI ethical use and perceived AI ethics. Specifically, higher AI literacy was associated with greater AI ethical use ($\beta = 0.254$, $t = 2.792$, $p = 0.005$), supporting H1. AI literacy also had a strong positive effect on perceived AI ethics ($\beta = 0.732$, $t = 16.287$, $p < 0.001$), supporting H2. In addition, perceived AI ethics had a significant positive effect on AI ethical use ($\beta = 0.571$, $t = 7.097$, $p < 0.001$), supporting H3. Among the three paths, the effect of AI literacy on perceived AI ethics was the strongest, suggesting that AI literacy is a key determinant of students' ethical perceptions of AI, which in turn are associated with more ethical AI use.

Table 11. Results of hypothesis testing

Constructs	Hypothesis	Path	β	t-value	p-value	Decision
AI Literacy	H1	AIL → AIEU	0.254	2.792	0.005	Supported
AI Literacy	H2	AIL → PAIE	0.732	16.287	<0.001	Supported
Perceived AI Ethics	H3	PAIE → AIEU	0.571	7.097	<0.001	Supported

4.10. Hypothesis Testing of Indirect Effect (Mediation)

The indirect effect was assessed using the bootstrapping procedure in SmartPLS. The indirect effect of AI literacy on AI ethical use through perceived AI ethics was statistically significant ($\beta = 0.418$, $p < 0.001$), with a 95% bias-corrected confidence interval of [0.299, 0.550] that does not include zero (Table 12). Because the direct effect of AI literacy on AI ethical use also remained significant ($\beta = 0.254$, $p = 0.005$), perceived AI ethics partially mediates this relationship, supporting H4, as shown in Table 12.

Table 12. Results of indirect effects (Mediation)

Hypothesis	Path	β	t-value	p-value	95% Bias-Corrected CI	Decision
H4	AIL → PAIE → AIEU	0.418	6.353	<0.001	[0.299, 0.550]	Supported

5. DISCUSSION

The findings provide evidence that AI literacy and perceived AI ethics are important factors associated with AI ethical use among Cambodian undergraduate students. The model explained 53.6% of the variance in perceived AI ethics and 60.3% in AI ethical use, indicating moderate to high explanatory power. Perceived AI ethics had the strongest relationship with AI ethical use (β = 0.571), followed by AI literacy (β = 0.254), while AI literacy was strongly related to perceived AI ethics (β = 0.732). The significant mediating role of perceived AI ethics indicates that AI literacy is related to AI ethical use partly through students' ethical perceptions.

The positive relationship between AI literacy and AI ethical use is consistent with previous studies showing that AI-literate students are better able to understand AI capabilities and limitations, evaluate AI-generated information critically, and apply AI responsibly in academic settings (Adamoli et al., 2025; Bewersdorff et al., 2025). This finding extends the evidence to Cambodian undergraduates, who are increasingly exposed to generative AI tools but may differ in their experience and understanding of them. Developing AI literacy may therefore encourage more responsible AI practices.

The strong positive relationship between AI literacy and perceived AI ethics is consistent with previous research suggesting that AI literacy strengthens students' ability to recognize and evaluate ethical concerns related to AI (Pramod, 2025; Abayeva & Butabayeva, 2026). Similarly, Nurhaliza (2025) and Meneses (2026) reported positive associations between AI literacy and awareness of AI-related ethical issues. Students who understand how AI works, including its limitations, may be better positioned to recognize concerns about privacy, fairness, transparency, accountability, and the reliability of AI-generated information. AI literacy should thus be developed not only as a technical competency but also as a foundation for ethical awareness.

The relationship between perceived AI ethics and AI ethical use was the strongest in the model (β = 0.571) and is consistent with previous studies indicating that stronger ethical perceptions are associated with more responsible AI use (Goreta et al., 2024; Ghosh, 2025; Kong & Zhu, 2025; Febrianti et al., 2026). Compared with the relationship between AI literacy and AI ethical use (β = 0.254), this stronger association suggests that understanding how AI should be used responsibly may matter more than knowing how to use it. Universities should therefore strengthen students' ethical understanding of AI, not only their technical ability.

The significant mediating role of perceived AI ethics provides insight into how AI literacy may contribute to ethical AI use. This finding agrees with Toker Gökçe et al. (2024), who suggested that ethical perceptions can be a mechanism through which AI knowledge influences behavior, and aligns with Abayeva and Butabayeva (2026), who emphasized the role of AI literacy in developing ethical awareness. Similarly, research suggests that ethical understanding can help translate AI knowledge into responsible behavior (Xie et al., 2025; Pramod, 2025). In the Cambodian context, improving AI literacy alone may not be sufficient; students also need opportunities to connect their technical understanding with ethical considerations such as academic integrity, attribution, privacy, fairness, and critical evaluation of AI-generated content. Integrating AI literacy with AI ethics education may therefore be a more effective approach to promoting responsible AI use.

Overall, the findings are consistent with prior research while providing context-specific evidence from Cambodian higher education. AI literacy is related to both perceived AI ethics and AI ethical use, and perceived AI ethics plays an important role as both a direct predictor and a mediator. Cambodian universities should consider integrating AI literacy and ethics education into existing academic and digital-skills programs rather than treating them separately. Given the limited evidence on these relationships in Cambodia, this study provides a foundation for future research across different universities, fields of study, educational levels, and professional groups.

6. CONCLUSION

6.1. Conclusion

This study examined the relationships among AI literacy, perceived AI ethics, and ethical AI use among Cambodian undergraduate students. The findings showed that AI literacy was significantly associated with perceived AI ethics and ethical AI use, while perceived AI ethics was significantly associated with ethical AI use and mediated the relationship between AI literacy and ethical AI use. The model explained 53.6% of the variance in perceived AI ethics and 60.3% of the variance in ethical AI use. Perceived AI ethics played an important role in understanding students' ethical AI use. These findings suggest that educators and higher education institutions in Cambodia should consider integrating AI literacy and AI ethics education into teaching and learning activities.

Educators could provide guidance on responsible AI use, including evaluating AI-generated information, protecting privacy, acknowledging AI assistance, and maintaining academic integrity. Universities could also establish clear guidelines for ethical AI use and provide training to help students understand the ethical implications of AI in academic work. Such initiatives may help students develop the

knowledge and ethical awareness needed to use AI responsibly. Overall, this study provides evidence from the Cambodian higher education context, although the use of convenience sampling and participation from four universities may limit the generalizability of the findings.

6.2. Implications of the Study

This study offers practical implications for promoting responsible AI use in Cambodian higher education. The findings indicate that both AI literacy and perceived AI ethics foster ethical AI use, with perceived AI ethics exerting the stronger effect. This suggests that cultivating students' ethical awareness deserves particular attention, and that educational initiatives on AI should combine technical knowledge with ethical considerations. For the Ministry of Education, Youth and Sport (MoEYS), the findings point to the need for clear national guidelines and policy frameworks governing the use of AI in education. Such frameworks could address academic integrity, transparency, privacy, appropriate attribution, the use of AI-generated content, and the protection of intellectual property.

MoEYS could also support higher education institutions through professional development programs, training workshops, and awareness campaigns that strengthen both educators' and students' AI literacy and ethical awareness. Together, these efforts could promote more consistent AI practices across Cambodian higher education. At the institutional level, universities should establish clear policies on the acceptable use of AI in learning, teaching, assessment, and research. AI literacy and ethics could be integrated into curricula, student orientation programs, digital-skills training, and co-curricular activities. Educators should give students practical guidance on evaluating AI-generated information and on issues such as transparency, fairness, privacy, accountability, bias, intellectual property, and academic integrity.

Classroom activities, such as critically evaluating AI-generated content and discussing ethical scenarios, could further help students develop responsible AI-use practices. For students, the findings underscore the need to continuously develop both AI literacy and ethical awareness. Students should understand the capabilities and limitations of AI, evaluate AI-generated information critically rather than accepting it uncritically, and use AI in ways that uphold academic integrity, respect privacy and intellectual property, and maintain transparency about AI-assisted work. Developing these competencies will better prepare them to use AI responsibly in their studies and future professional environments.

6.3. Limitations and Future Research

This study provides insights into the relationships among artificial intelligence literacy, perceived AI ethics, and ethical AI use among Cambodian undergraduate students. However, several limitations should be acknowledged. First, the use of convenience sampling means that participants were recruited based on their accessibility and willingness to participate rather than through random selection, which may introduce sampling bias. Although the study included students from four universities, these institutions may not fully represent the diversity of higher education institutions in Cambodia. Therefore, the findings should be interpreted with caution and may not be generalizable to all Cambodian university students. Second, the higher proportion of female respondents may limit the representativeness of the sample and the applicability of the findings across genders. Third, the cross-sectional design does not support causal conclusions.

Fourth, the study relied on self-reported data collected through a single questionnaire, which may introduce response bias, including social desirability bias, particularly given the ethical nature of the constructs. Although collinearity was assessed using variance inflation factors (VIF), this assessment alone does not establish the absence of common method bias (CMB). Therefore, potential CMB may have affected the estimated relationships among the study variables. Fifth, although partial least squares structural equation modeling (PLS-SEM) was appropriate for the study's prediction-oriented objectives, the results may differ from those obtained using covariance-based structural equation modeling (CB-SEM). Finally, the model excluded other potentially relevant factors, including artificial intelligence self-efficacy, digital literacy, academic integrity, institutional policies, and ethical climate.

Future research should consider probability sampling across a broader range of public and private universities, with greater demographic balance, to improve sample representativeness and the generalizability of the findings. Including postgraduate students, educators, and professionals could provide a broader understanding of ethical AI use. Longitudinal or mixed-method designs could offer deeper insights into ethical decision-making over time. Future studies should also assess CMB using appropriate procedures, such as procedural remedies in questionnaire design, Harman's single-factor test, or a marker variable approach, and consider collecting data from multiple sources. In addition, researchers could apply CB-SEM or compare CB-SEM with PLS-SEM to examine the robustness of the findings. Finally, the model could be extended by incorporating additional factors such as artificial intelligence self-efficacy, digital literacy, academic integrity, institutional policies, ethical climate, and prior AI experience.

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ETHICAL STATEMENT

The study involved human participants and was conducted in accordance with applicable ethical principles for research involving human participants. Participation was voluntary, and participants were informed about the purpose of the study and their right to participate. Informed consent was obtained from all participants before data collection. The responses were collected anonymously and used solely for academic research purposes.

AI USE STATEMENT

The author used Grammarly solely to improve linguistic clarity and grammatical accuracy in selected sections of the manuscript. ChatGPT was consulted solely to obtain explanations and clarification of statistical concepts, formulas, and methodological procedures related to partial least squares structural equation modeling, including effect size, coefficient of determination, predictive relevance, reliability measures, and SmartPLS procedures. These tools were not used to conduct the statistical analyses, make research or methodological decisions, interpret the study findings, or develop the conclusions. The author takes full responsibility for the research design, data analysis, interpretation of results, and all content presented in this manuscript.

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