The Influence of AI Training Program and AI Literacy on Ethical AI Use among AI-Trained Undergraduate Students: Evidence from Higher Education in Cambodia

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ABSTRACT

Purpose of the study: This study aims to investigate the relationships among AI training program, AI literacy, and ethical AI use among AI-trained undergraduate students in Cambodia. Specifically, it examines the effects of AI training program on AI literacy and ethical AI use, as well as the mediating role of AI literacy.

Methodology: A quantitative correlational research design was employed using data collected from 300 AI-trained undergraduate students at BELTEI International University through convenience sampling. The data were analyzed using Microsoft Excel, SPSS, and SmartPLS. Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to assess the measurement model, structural model, and mediation effect.

Main Findings: The findings found that AI training program significantly enhanced AI literacy and ethical AI use, while AI literacy positively influenced ethical AI use. The structural model explained 33.7% of the variance in AI literacy and 45.4% of the variance in ethical AI use. Additionally, AI literacy significantly mediated the relationship between the AI training program and ethical AI use.

Novelty/Originality of this study: This study contributes to responsible AI education in Cambodian higher education by integrating AI training program, AI literacy, and ethical AI use into a PLS-SEM model. It highlights AI literacy as a significant mechanism linking AI training experiences with ethical AI use among undergraduate students. The study extends social science education research by emphasizing the role of higher education in enhancing students' AI-related knowledge and ethical technology practices. The findings also provide implications for educators and institutions designing AI training programs that promote both technological competence and ethical AI use. Future studies are encouraged to extend this model by examining additional factors and diverse educational contexts.

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1. INTRODUCTION

Artificial Intelligence (AI) has speedily transformed higher education by boosting learning efficiency, personalization, and access to educational resources [1], [2]. The integration of AI-supported learning tools, such as adaptive learning systems and intelligent tutoring platforms, has led to improved student engagement, motivation, critical thinking, and independent learning experiences across different educational settings [3]–[6].

These advances underline the growing importance of AI adoption in enhancing educational practices and outcomes. However, despite these advantages, the increasing use of AI in higher education raises concerns about students' responsible and ethical use of AI technologies. The rapid integration of AI into higher education displays social and ethical challenges related to students' academic behavior, social responsibility, and academic integrity, including over-reliance on AI-generated content and difficulties in evaluating AI outputs [4].

These concerns may indicate that AI education should extend beyond technical competence to foster responsible attitudes, ethical awareness, critical judgment, and accountability in AI use. From an educational perspective, developing these competencies can support students' responsible participation in academic communities and promote more ethical use of AI technologies [2], [5]. Previous research has identified challenges like over-reliance on AI tools, diminished independent thinking, issues with academic integrity, and inadequate assessment of AI-generated information [4], [7], [8]. Consequently, many institutions have introduced AI training programs to equip students with the knowledge and skills needed to use AI technologies effectively and responsibly. These training initiatives are delivered through various modes, including online, face-to-face, and hybrid formats, and generally aim to improve students' understanding of AI concepts, practical applications, and ethical considerations [9].

Previous research has shown that participation in AI training programs enhances students' understanding of AI concepts, strengthens their AI literacy, and increases their confidence in using AI technologies [10]. Targeted AI training has also been found to promote more informed and responsible interactions with AI systems by helping learners better understand AI's capabilities and limitations, thereby supporting more autonomous and appropriate AI use [10]. As AI training programs enhance students' AI-related knowledge and competencies, developing AI literacy has become increasingly important for enabling students to understand AI's capabilities, limitations, and ethical implications in academic settings. AI literacy is widely recognised as a key factor in promoting responsible AI-related behaviours among university students [11], [12]. Students with higher AI literacy are more likely to critically evaluate AI-generated outputs, recognise potential risks, and use AI tools more responsibly and ethically [11], [12].

Hence, AI literacy extends beyond technical knowledge to support students' broader educational and social development [10]. Understanding AI's capabilities, limitations, and ethical implications can strengthen critical judgment, responsible decision-making, and accountability. These competencies are also relevant to character education and social learning, where students develop responsible behaviors through knowledge, reflection, and engagement with ethical and social norms [10]. Thus, AI literacy may support not only effective AI use but also responsible and ethical practices among university students. Nevertheless, previous studies have primarily examined AI training in relation to students' AI knowledge, skills, confidence, or general technology adoption [10], while less attention has been given to how AI literacy may link AI training to ethical AI use.

Evidence on this relationship also remains limited in developing-country higher education contexts, particularly among students who have experienced formal AI training. This gap highlights the need to examine how educational interventions can foster responsible and ethical AI practices among university students. Given the rapid expansion of AI in higher education, understanding how students can be prepared for responsible and ethical AI use is progressively vital. This study is novel in examining AI literacy as a mediating mechanism between AI training program and ethical AI use among AI-trained undergraduate students in Cambodia. Therefore, this study aims to examine the effects of AI training programs on AI literacy and ethical AI use, the influence of AI literacy on ethical AI use, and the mediating role of AI literacy in this relationship.

2. LITERATURE REVIEW

2.1. Artificial Intelligence Adoption in Higher Education

AI has become increasingly integrated into higher education by supporting teaching, learning, research, and administrative activities [13]. AI applications, including personalized learning systems, intelligent tutoring tools, natural language processing, and predictive analytics, have enhanced learning effectiveness, student engagement, and access to educational resources [13], [14]. A global survey by Kelly [15] involving 3,839 university students across 16 countries found that AI is widely used for academic purposes, particularly information searching, writing support, summarization, and content generation. Despite these benefits, the increasing adoption of AI has raised concerns regarding students' responsible and ethical use of AI technologies.

Previous studies have reported that excessive dependence on AI may reduce critical thinking, weaken independent learning, and create challenges related to academic integrity and responsible learning behaviours across different higher education contexts [16]–[19]. These concerns underscore the importance of identifying factors that promote the ethical use of AI among university students. To address these issues, higher education institutions have increasingly introduced AI training programs, including online, face-to-face, and hybrid formats, to equip students with essential AI knowledge and skills for effective and ethical AI use. For instance, existing studies have demonstrated that structured AI training initiatives can enhance students' understanding of AI concepts, improve their AI literacy, and encourage more responsible and informed interactions with AI technologies [9], [10].

Moreover, AI literacy has been observed as a substantial factor in promoting responsible AI-related behaviours. Students with higher AI literacy are more capable of understanding AI capabilities and limitations, critically evaluating AI-generated information, and applying AI technologies appropriately in academic settings [20]–[23]. In higher education, ethical AI use represents the students' ethical decision-making, integrity, and responsible participation in academic communities [12], [17]. AI literacy may therefore extend beyond technical competence by supporting responsible behavior when students interact with AI technologies. These behaviors align with broader educational goals of ethical awareness, responsible decision-making, and appropriate conduct in academic contexts [12], [17]. However, empirical evidence examining the relationship between AI literacy and the ethical use of AI remains limited, particularly in developing higher education contexts. In Cambodia, research on AI in higher education has mainly focused on AI adoption, students' perceptions, learning outcomes, and AI readiness [24]–[27].

In Cambodia, research on AI in higher education has mainly focused on AI adoption, students' perceptions, learning outcomes, and AI readiness [24]–[27]. Although previous studies have provided valuable insights into AI adoption and readiness in higher education, empirical evidence on the factors influencing ethical AI use among AI-trained undergraduate students remains limited. In particular, limited research has examined how AI training programs enhance AI literacy and how AI literacy contributes to ethical AI use, especially in Cambodia. Therefore, this study investigates the effects of AI training program on AI literacy, the influence of AI literacy on ethical AI use, the direct effect of AI training programs on ethical AI use, and the mediating role of AI literacy among AI-trained undergraduate students in Cambodia using the PLS-SEM approach. The study contributes by extending the understanding of responsible AI use and providing empirical evidence from Cambodian higher education, offering insights into how AI training initiatives can foster AI literacy and promote ethical AI practices among university students.

2.2. Theoretical Foundations

This study is theoretically guided by Social Cognitive Theory (SCT), proposed by Bandura [28], which explains that individuals' behaviours are shaped through the interaction between environmental influences, cognitive factors, and personal actions. In the context of AI use, AI training programs represent an essential environmental factor that provides students with opportunities to develop AI-related knowledge, skills, and awareness. Through structured learning experiences, an AI training program can enhance students' AI literacy, which represents a cognitive capability that enables them to understand AI technologies, evaluate AI-generated information, and make appropriate decisions regarding AI applications. Therefore, students with higher AI literacy are expected to demonstrate more responsible and ethical AI use behaviours.

2.3. Hypothesis Development

2.3.1. AI Training Program and AI Literacy

AI training program provides structured learning experiences that enhance students' knowledge, skills, and understanding of AI technologies [29]. From the perspective of SCT Bandura [28], AI training programs represent an environmental factor that supports the development of cognitive capabilities such as AI literacy. Previous studies have shown that targeted AI training can improve AI understanding, strengthen AI literacy, and promote more responsible interactions with AI technologies [9], [10]. Therefore, this study proposes the following hypothesis: **H1:** AI training program has a positive effect on AI literacy among AI-trained undergraduate students in Cambodia.

2.3.2. AI Literacy and AI Ethical Use

AI literacy refers to individuals' ability to understand, evaluate, and effectively apply AI technologies while considering their ethical implications [30], [31]. Beyond technical skills, AI literacy can foster students' ethical awareness, critical evaluation, and responsible decision-making when using AI in academic contexts [10], [21]. These competencies may enable students to consider the consequences of AI use, recognize potential risks, and act with greater accountability toward their academic communities [10], [21]. It includes knowledge of AI concepts, critical evaluation skills, and awareness of responsible AI practices. Previous studies have shown that students with stronger AI literacy are more likely to use AI tools appropriately, evaluate AI-generated outputs critically, and follow ethical principles when applying AI in academic contexts [32]–[34]. Therefore, this study proposes the following hypothesis: **H2:** AI literacy has a positive effect on ethical AI use among AI-trained undergraduate students in Cambodia.

2.3.3. AI Training Program and Ethical AI Use

An AI training program plays a substantial role in fostering the knowledge, skills, and awareness required for responsible AI adoption [35]. Through structured training, students can gain a deeper understanding of AI capabilities, limitations, ethical risks, and appropriate practices for evaluating AI-generated outputs [36]. Previous research suggests that AI-related training can influence users' decision-making processes and encourage more responsible interactions with AI systems [36], [37]. Therefore, AI training programs are expected to enhance ethical AI use by equipping undergraduate students with the necessary competencies to apply AI technologies responsibly and ethically. Accordingly, this study proposes the following hypothesis: **H3:** AI training programs have a positive effect on ethical AI use among AI-trained undergraduate students in Cambodia.

2.3.4. Mediating Role of AI Literacy

AI literacy may serve as a mechanism that explains how AI-related learning experiences influence ethical AI use [38]. AI training programs provide students with essential AI knowledge and skills, while AI literacy enables them to understand AI capabilities, evaluate AI-generated information, and apply AI technologies responsibly [35], [39]. Previous studies have shown that AI literacy can mediate the relationship between AI-related educational experiences and behavioural outcomes. For example, Florendo [35] found that AI literacy mediated the relationship between AI ethics instruction and ethical preparedness among graduate students. Similarly, Wang and Cao [39] reported that AI literacy partially mediated the relationship between AI-empowered learning experiences and intercultural competence. Therefore, this study proposes the following hypothesis: **H4:** AI literacy mediates the relationship between the AI training program and ethical AI use among AI-trained undergraduate students in Cambodia.

2.4. Conceptual Framework

Drawing on SCT and prior studies, this study proposes a conceptual framework examining the relationships among AI training programs, AI literacy, and ethical AI use among AI-trained undergraduate students in Cambodia. The framework positions AI training programs as an environmental factor that enhances AI literacy, which subsequently influences ethical AI use. It examines the effects of AI training programs on AI literacy, AI literacy on ethical AI use, the direct effect of AI training programs on ethical AI use, and the mediating role of AI literacy, as illustrated in Figure 1.

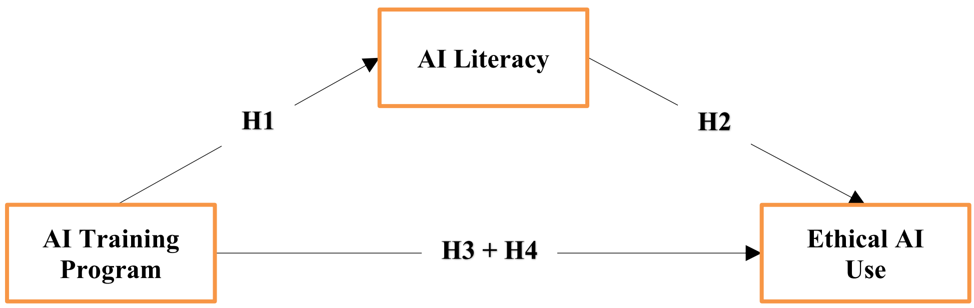

Figure 1. Conceptual Framework

3. RESEARCH METHOD

3.1. Research Design

This study employed a quantitative correlational research design to examine the relationships among AI training programs, AI literacy, and ethical AI use among AI-trained undergraduate students in Cambodia. The quantitative approach enabled the measurement of variables, testing of hypothesized relationships, and analysis of the mediating role of AI literacy using the boostrapping. Data were collected through a survey questionnaire assessing students' experiences with AI training, AI literacy, and ethical AI use. This design was appropriate for addressing the research objectives and testing the proposed model.

3.2. Sample and Sampling Methods

Since the total population of undergraduate students with AI training experience was unknown but considered sufficiently large, Cochran's formula was applied to determine the minimum required sample size: $n = p(1-p)Z^2/e^2$ [40]. The calculation was based on a 95% confidence level ($z = 1.96$), a 5% margin of error ($e = 0.05$), and an estimated population proportion of 0.10 ($p = 0.10$), resulting in a minimum sample size of 139 respondents [40]. The final sample consisted of 300 AI-trained undergraduate students from BELTEI International University (Campus 1 and Campus 2) in Phnom Penh, Cambodia, selected using convenience sampling [41]. The sample size exceeded the minimum requirement for PLS-SEM, providing sufficient statistical power and reliable parameter estimates [42].

Therefore, the final sample was considered adequate for evaluating both the measurement and structural models. The respondents were selected based on their participation in AI-related training programmes, including virtual, face-to-face, and both (virtual or face-to-face) training modes, enabling them to provide relevant assessments of AI literacy and ethical AI use based on their training experiences. Including students with diverse training backgrounds allowed the study to capture variations in AI learning experiences and examine the proposed relationships among the research constructs. However, the use of convenience sampling may limit the generalisability of the findings beyond the study context.

3.3. Research Instruments

The questionnaire consisted of demographic information and measurement items adapted from previous studies, as presented in Table 1. The items were modified to suit the Cambodian context and translated into Khmer using a back-translation process by bilingual researchers. A pilot test was conducted to ensure clarity and appropriateness before data collection. A bilingual (Khmer–English) questionnaire was used, and all items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) [41]. Mean scores were interpreted based on the classification proposed by [43]. Finally, data normality was assessed using skewness and kurtosis, with values between −2 and +2 considered acceptable [44].

Table 1. A Summary of The Construct Measurement

Constructs	No. of items	Sources
AI Training Programs	AITP1 → AITP4	[45], [2]
AI Literacy	AIL1 → AIL5	[46], [47]
Ethical AI Use	EAIU1 → EAIU5	[45], [12]

3.4. Data Collection Procedures

Data collection was conducted in two phases at BELTEI International University (Campus 1 and Campus 2). In the first phase, a pilot study was conducted with 100 fourth-year undergraduate students who had experience using AI tools. The purpose of the pilot study was to evaluate the clarity, content validity, and internal consistency of the questionnaire items. Based on the pilot findings, minor revisions were made to improve the wording and measurement quality of the instrument before the main survey. In the second phase, the final questionnaire was administered to 300 undergraduate students who had participated in AI training programmes, including virtual, face-to-face, and both (virtual or face-to-face) training modes.

Data were collected using a Google Forms questionnaire distributed through Telegram. Participation was voluntary, and respondents were informed of the study's objectives before providing informed consent. The anonymity and confidentiality of all participants were strictly maintained throughout the research process. Institutional approval was obtained prior to data collection. The collected data were subsequently analysed using regression analysis to examine the effects of the AI training programme on AI literacy, the influence of AI literacy on ethical AI use, and the mediating role of AI literacy in the relationship between the AI training programm and ethical AI use.

3.5. Research Procedures

The research followed a rigorous process, beginning with instrument adaptation and Khmer back-translation, followed by a pilot study and questionnaire revision. The revised questionnaire was then administered to AI-trained undergraduate students through Google Forms. After data screening and preparation, EFA and PLS-SEM were conducted to assess the measurement and structural models. Bootstrapping with 5,000 subsamples was subsequently used to test the significance of the mediating effects.

3.6. Data Analysis Method

The data were analysed using Microsoft Excel 2015, IBM SPSS Statistics 27, and SmartPLS 3. Microsoft Excel was used for data coding, screening, and preparation, whereas SPSS was employed to generate descriptive statistics, evaluate internal consistency, and assess EFA. EFA was conducted using principal component analysis with varimax rotation to identify the underlying factor structure and refine the measurement items [48]. The adequacy of the data for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity [49]. Factors were retained based on KMO values above 0.60, a significant Bartlett's test ($p < 0.05$), eigenvalues greater than 1.0, factor loadings of at least 0.60, cross-loadings below 0.40, and cumulative explained variance exceeding 60% [49], [50]. Internal consistency was evaluated using Cronbach's alpha ($\alpha \geq 0.60$) and the Average Inter-Item Correlation (AIIC), with acceptable values ranging from 0.30 to 0.70 [51].

Additionally, given the single-source, self-reported data, Harman's single-factor test was conducted to assess common method bias, with values below 50% indicating no serious bias [52]. The hypothesised relationships were examined using PLS-SEM in SmartPLS following the two-stage procedure recommended by

[42]. The measurement model was assessed through indicator reliability, internal consistency reliability, convergent validity, and discriminant validity using outer loadings, Cronbach's alpha, composite reliability (CR), rho_A, average variance extracted (AVE), the Fornell–Larcker criterion, and the heterotrait–monotrait ratio (HTMT). The structural model was subsequently evaluated by examining collinearity (VIF), path coefficients (β), effect sizes (f^2), coefficients of determination (R^2), predictive relevance (Q^2), and bootstrapping to determine the significance of both direct and indirect (mediating) effects, as shown in Table 2 [42], [53]–[56].

Table 2. Evaluation Criteria for PLS-SEM Analysis

Model Assessment	Criteria	Sources
Outer loading	≥ 0.70	[42]
α	≥ 0.70	[42]
CR	≥ 0.70	[42]
AVE	≥ 0.50	[54]
HTMT ratio	< 0.85 or < 0.90	[55]
VIF	< 3.00	[56]
β	t-value > 1.96 and p-value < 0.05	[42]
R^2	0.25 = weak, 0.50 = moderate, and 0.75 = substantial	[42]
f^2	0.02 = small, 0.15 = medium, and 0.35 = large	[53]
Q^2	$Q^2 > 0$	[42]
Bootstrapping	5,000 subsamples	[42]

4. RESULTS AND DISCUSSION

4.1. Results

The results are presented in several sections. The analysis begins with demographic characteristics, descriptive statistics, EFA, and reliability assessment. Next, the measurement model is evaluated using PLS-SEM through indicator reliability, internal consistency, convergent validity, and discriminant validity. Finally, the structural model is assessed using collinearity, common method bias, R^2, f^2, Q^2, and hypothesis testing, including direct and mediation analyses.

4.1.1. Respondent Demographics

Table 3 exhibits the demographic and AI-related characteristics of the 300 respondents. The sample included slightly more female (54.3%) than male (45.7%) students, with most aged 18–23 years (92.6%), indicating a predominantly young undergraduate sample. ChatGPT was the most commonly used AI tool (74.3%), followed by Gemini (11.3%), Microsoft Copilot (5.7%), DeepSeek (5.0%), and other tools (3.7%). Regarding training experience, most respondents had participated in virtual AI training (72.3%), followed by face-to-face (17.3%) and both formats (10.3%).

Table 3. Demographic Characteristics of The Respondents

Demographic	Description (n = 300)	Frequency	Percentage (%)
Gender	Female	163	54.3
	Male	137	45.7
	Total	300	100
Age	18–20 years old	148	49.3
	21–23 years old	130	43.3
	24–26 years old	12	4.0
	Above 26 years old	10	3.3
	Total	300	100
Primary AI Tool Used	ChatGPT	223	74.3
	Gemini	34	11.3
	Microsoft Copilot	17	5.7
	DeepSeek	15	5.0
	Others	11	3.7
	Total	300	100
Training Experience	Virtual (Online)	217	72.3
	Face-toFace	52	17.3
	Both (Online and Face-to-Face)	31	10.3
	Total	300	100

4.1.2. Descriptive Statistics

Table 4 displays the descriptive statistics and distribution of the three study constructs. The mean values ranged from 3.5658 to 3.8273, indicating general agreement with the statements on AI Training Program, AI Literacy, and Ethical AI Use. The standard deviations indicated moderate variation in responses, while skewness and kurtosis values fell within the acceptable ±2 range, demonstrating no substantial departure from normality.

Table 4. Results of Descriptive Statistics

Constructs	Minimum	Maximum	M	SD	Skewness	Kurtosis	LA
AI Training Program	1.00	5.00	3.5658	0.71273	-0.812	1.652	Agree
AI Literacy	1.25	5.00	3.7417	0.64165	-0.753	1.237	Agree
Ethical AI Use	1.00	5.00	3.8273	0.69353	-0.937	1.890	Agree

Note. M = Mean; SD = Standard Deviation; LA = Level of Agreement

4.1.3. Exploratory Factor Analysis

An exploratory factor analysis (EFA) was conducted using an independent pilot sample of 100 undergraduate students, consisting of Year 3 and Year 4 students majoring in Accounting, International Business, Marketing, Finance and Banking, and General Management. This pilot dataset was collected separately from the main study sample to examine the underlying factor structure and refine the measurement items. The results indicated satisfactory sampling adequacy for all constructs. Specifically, the KMO values for AI Training Program, AI Literacy, and Ethical AI Use were 0.797, 0.690, and 0.826, respectively, supporting the suitability of the data for factor analysis. The extracted factors explained 62.599%, 64.458%, and 62.804% of the total variance, respectively. All retained items demonstrated acceptable factor loadings ranging from 0.644 to 0.975.

The EFA results demonstrated that all retained indicators showed acceptable factor loadings and adequately represented their respective constructs. The AI Literacy construct consisted of five items with factor loadings ranging from 0.695 to 0.975. Similarly, the AI Training Program construct included four items with factor loadings ranging from 0.770 to 0.801, while the Ethical AI Use construct comprised five items with factor loadings between 0.644 and 0.855. Overall, the EFA findings confirmed the satisfactory factor structure of all constructs, providing empirical support for the measurement items and establishing a reliable foundation for subsequent reliability testing and hypothesis analysis, as presented in Table 5.

Table 5. Exploratory Factor Analysis Results

Constructs		Factor Analysis			
		FL	KMO	E	Cu%
	AI Training Program				
AITP1	An AI training program provides clear guidance on the appropriate use of AI tools.	0.770	0.797	2.504	62.599
AITP2	The AI training program improves my understanding of how to apply AI tools in learning activities.	0.793			
AITP3	An AI training program explains the ethical principles for using AI tools in academic activities.	0.800			
AITP4	An AI training program helps me understand the capabilities, limitations, and potential risks of AI technologies.	0.801			
	AI Literacy				
AIL1	I am familiar with the basic concepts of AI and its responsible applications in higher education.	0.975	0.690	1.042	64.458
AIL2	I can explain how AI tools generate information and understand the importance of transparency in AI systems.	0.722			
AIL3	I know how to use AI tools effectively while protecting personal and academic data.	0.791			
AIL4	I am aware of the ethical risks and limitations associated with using AI tools for academic purposes.	0.695			
AIL5	I critically evaluate AI-generated content to ensure its accuracy, reliability, and ethical appropriateness before use.	0.741			
	Ethical AI Use				
EAIU1	I use AI tools to assist my learning while maintaining academic integrity standards.	0.847	0.826	3.140	62.804
EAIU2	I critically examine and verify AI-generated information before using it in my academic work.	0.644			
EAIU3	I use AI tools to generate ideas while preserving my own creativity and originality.	0.808			

EAIU4	I obey academic guidelines when using AI tools in my academic work.	0.855
EAIU5	I use AI tools appropriately and ethically based on my academic needs.	0.790

4.1.4. Reliability Analysis

Table 6 presents the reliability analysis of the refined scales following EFA. AI Training Program and Ethical AI Use demonstrated good internal consistency, with Cronbach's alpha values of 0.801 and 0.849, respectively, while AI Literacy showed a marginally acceptable value of 0.601 for exploratory research. The AIIC values ranged from 0.300 to 0.529, supporting the suitability of the refined scales for subsequent PLS-SEM analysis.

Table 6. Reliability Analysis of Measurement Items

Constructs	No. of item	Cronbach's Alpha	Interpretation	AIIC	Constructs
AI Training Program	4	0.801	Good	0.501	AI Training Program
AI Literacy	5	0.601	Questionable	0.300	AI Literacy
Ethical AI Use	5	0.849	Good	0.529	Ethical AI Use

Note. Cronbach's α: 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 ≤ AIIC ≤ 0.70.

4.1.5. Common Method Variance

Harman's single-factor test was conducted to assess potential common method bias in the self-reported data (n = 300). Using an unrotated principal component analysis, the first factor explained 44.930% of the total variance, below the 50% threshold, indicating no serious common method bias.

4.1.6. Measurement Model Assessment

Table 7 presents the measurement model assessment results. All retained items showed satisfactory outer loadings (0.734–0.851), exceeding the 0.70 threshold. AIL4 (Outer loading = 0.625) was removed because its loading was below the recommended criterion, and its removal improved the overall measurement quality, particularly discriminant validity. This decision ensured that the remaining items provided a stronger representation of the AI literacy construct and enhanced the validity of the measurement model. All constructs demonstrated acceptable reliability and convergent validity, with Cronbach's alpha (0.772–0.863), CR (0.854–0.901), and AVE (0.594–0.647) above the recommended criteria.

Table 7. Measurement Model Assessment

Constructs	Item	Outer Loading	Cronbach's Alpha	rho_A	CR	AVE
AI Training Program	AITP1	0.786	0.772	0.774	0.854	0.594
	AITP2	0.793				
	AITP3	0.770				
	AITP4	0.796				
AI Literacy	AIL1	0.734	0.795	0.800	0.866	0.618
	AIL2	0.796				
	AIL3	0.766				
	AIL5	0.786				
Ethical AI Use	EAIU1	0.811	0.863	0.868	0.901	0.647
	EAIU2	0.736				
	EAIU3	0.809				
	EAIU4	0.811				
	EAIU5	0.851				

4.1.7. Discriminant Validity Assessment

Table 8 presents the HTMT results for assessing discriminant validity. All HTMT values ranged from 0.599 to 0.802, below the recommended threshold of 0.85, confirming satisfactory discriminant validity. These results indicate that the study constructs are sufficiently distinct from one another.

Table 8. HTMT Criterion

Constructs	AI Training Program	AI Literacy	Ethical AI Use
AI Training Program	–		
AI Literacy	0.735	–	
Ethical AI Use	0.802	0.599	–

Additionally, Table 9 shows the Fornell–Larcker criterion for further assessing discriminant validity. The diagonal √AVE values (0.771–0.804) were higher than the corresponding inter-construct correlations (0.502–0.658) for each construct. These results confirm that each construct shares greater variance with its own indicators than with other constructs, supporting satisfactory discriminant validity.

Table 9. Fornell–Larcker Criterion and Correlation Matrix

Constructs	AI Training Program	AI Literacy	Ethical AI Use
AI Training Program	0.771		
AI Literacy	0.581**	0.786	
Ethical AI Use	0.658**	0.502**	0.804

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

4.1.8. Structural Model Assessment

Figure 2 presents the structural model of the hypothesized relationships among the AI Training Program, AI Literacy, and Ethical AI Use estimated using the PLS algorithm in SmartPLS. The structural model was subsequently evaluated using collinearity, explanatory power (R^2), predictive relevance (Q^2), and hypothesis testing, with the significance of the path coefficients (β) assessed through the bootstrapping procedure.

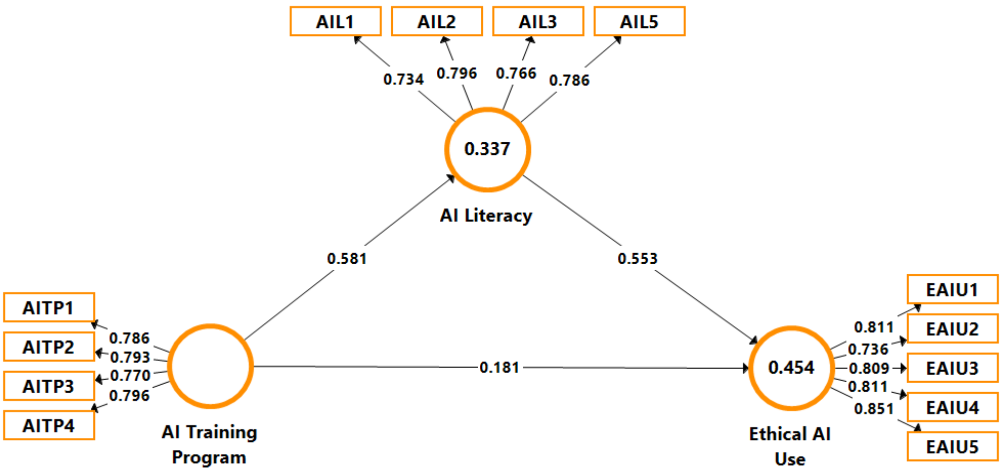

Figure 2. Structural Model Estimated Using The PLS Algorithm

4.1.9. Collinearity and Common Method Bias Assessment

The inner VIF values presented in Table 10 ranged from 1.000 to 1.508, which were well below the recommended threshold of 5.00. These results indicate that multicollinearity was not a concern, confirming that the predictor constructs did not exhibit collinearity issues in the structural model.

Table 10. Collinearity and Common Method Bias Assessment

Predictor Construct	Endogenous Construct	VIF (< 0.30)	Interpretation
AI Training Program	AI Literacy	1.000	No Common Method Bias
AI Training Program	Ethical AI Use	1.508	No Common Method Bias
AI Literacy	Ethical AI Use	1.508	No Common Method Bias

4.1.10. Structural Model Quality Assessment

Table 11 presents the structural model's explanatory power, predictive relevance, and effect sizes. AI Training Program explained 33.7% of the variance in AI Literacy (R^2 = 0.337; Q^2 = 0.195), while AI Training Program and AI Literacy jointly explained 45.4% of the variance in Ethical AI Use (R^2 = 0.454; Q^2 = 0.287). The positive Q^2 values indicate predictive relevance of the model. Regarding effect sizes, the AI Training Program had a large effect on AI Literacy ($f^2 = 0.508$), AI Literacy had a large effect on Ethical AI Use ($f^2 = 0.371$), whereas the AI Training Program had a small effect on Ethical AI Use ($f^2 = 0.040$). These findings suggest that the AI Training Program contributes strongly to AI Literacy, while AI Literacy plays a significant role in explaining Ethical AI Use.

Table 11. Structural Model Quality Assessment

Endogenous Constructs	R^2	Adjusted R^2	Q^2	Exogenous	f^2	Effect Size
AI Literacy	0.337	0.335	0.195	AI Training Program	0.508	Large
Ethical AI Use	0.454	0.450	0.287	AI Literacy	0.371	Large
	–	–	–	AI Training Program	0.040	Small

4.1.11. Hypothesis Testing of Direct Effect

Table 12 exhibits the results of the direct-effect hypothesis testing. AI Training Program had a significant positive effect on AI Literacy ($\beta = 0.581$, t-value = 12.555, p-value < 0.001), while AI Literacy significantly and positively influenced Ethical AI Use ($\beta = 0.553$, t-value = 10.290, p-value < 0.001). AI Training Program also had a significant positive effect on Ethical AI Use ($\beta = 0.181$, t-va;ue = 2.634, p-value = 0.008). These findings support H1, H2, and H3, indicating that AI training is associated with stronger AI literacy and ethical AI use, while AI literacy is an important factor in promoting ethical AI use.

Table 12. Results of Hypothesis Testing

Constructs	Hypothesis	Path Relationships	β	t-value	p-value	Results
AI Training Program	H1	AITP → AIL	0.581	12.555	0.000	Supported
AI Literacy	H2	AIL → EAIU	0.553	10.290	0.000	Supported
AI Training Program	H3	AITP → EAIU	0.181	2.634	0.008	Supported

Note. * = p < .05; ** = p < .01; *** = p < 0.001

4.1.12. Hypothesis Testing of Mediating Effect

The mediation analysis using the bootstrapping procedure shows that AI Literacy significantly mediates the relationship between AI Training Program and Ethical AI Use ($\beta = 0.321$, t-value = 7.326, p-value < 0.001). The 95% BCa confidence interval [0.244, 0.415] does not include zero, confirming a significant indirect effect. Since the indirect effect ($\beta = 0.321$) is stronger than the direct effect of the AI Training Program on Ethical AI Use ($\beta = 0.181$), AI Literacy plays an important mediating role, as the AI Training Program primarily enhances Ethical AI Use by improving students' AI Literacy, which helps translate training experiences into responsible AI practices, as presented in Table 13.

Table 13. Results of The Mediating Effect Analysis

Hypothesis	Indirect Relationship	β	t-value	p-value	95% BCa CI	Mediation Type	Results
H4	AITP → AIL→ EAIU	0.321	7.326	0.000	[0.244, 0.415]	Partial	Supported

4.2. Discussion

This study aimed to explore the relationships among the AI training program, AI Literacy, and ethical AI use among AI-trained undergraduate students in Cambodia. The results showed that the AI training program significantly improved AI literacy. The findings align with previous research demonstrating that structured AI training can enhance students' understanding and literacy of AI. This finding suggests that AI training provides relevant knowledge and learning experiences that strengthen students' ability to understand and engage with AI technologies. From the perspective of Social Cognitive Theory (SCT), the AI Training Program represents an environmental influence that can support the development of students' cognitive capabilities, particularly AI literacy. In the Cambodian higher education context, these results suggest that structured AI training can provide undergraduate students with learning experiences that strengthen their AI knowledge and support more effective engagement with AI technologies.

AI literacy significantly and positively influenced ethical AI use, supporting previous literature showing that students with higher AI literacy can better evaluate AI-generated information, recognize risks, and use AI responsibly. Regarding SCT, AI literacy represents a cognitive capability that helps students understand AI, evaluate its use, and make responsible decisions when interacting with AI technologies. In the Cambodian higher education context, stronger AI literacy may enhance students' critical judgment, accountability, and responsible decision-making. These competencies also support academic integrity by encouraging students to verify AI-generated information, maintain originality, and follow institutional guidelines. Hence, AI literacy contributes to social science education by promoting ethical awareness and responsible behavior.

The AI training program also significantly influenced ethical AI use, suggesting that structured training can directly encourage students to use AI technologies more responsibly. This finding is consistent with previous research showing that AI-related training can improve students' awareness of responsible and ethical AI practices. From the perspective of SCT, AI training provides an environmental learning experience that can shape students' behavioral practices. In the Cambodian higher education context, structured training may help undergraduate students develop responsible AI practices by combining technical knowledge with ethical awareness and social responsibility. Thus, AI training should address not only how to use AI but also how to use it appropriately and responsibly in academic settings.

The mediating role of AI literacy further indicates that training experiences influence ethical AI practices partly by strengthening students' ability to understand, evaluate, and responsibly apply AI. Regarding SCT, this relationship reflects the interaction between environmental influences, cognitive abilities, and behavioral outcomes. In this study, the AI training program represents the environmental factor, AI literacy reflects students' cognitive capabilities, and ethical AI use indicates the resulting behavior. In the Cambodian higher education context, strengthening AI literacy through structured training may help undergraduate students translate AI knowledge into more responsible and ethical AI practices. Thus, AI literacy serves as an important mechanism through which AI training experiences can contribute to responsible and ethical AI practices.

These findings have practical implications for Cambodian higher education. Universities and educators should design AI training programs that integrate AI literacy, ethical awareness, academic integrity, and responsible decision-making. Such initiatives can help students develop not only AI-related competencies but also responsible behaviors needed for ethical participation in academic communities. The study extends AI education beyond technological competence by highlighting the social and behavioral dimensions of responsible AI use. For the Ministry of Education, Youth and Sport (MoEYS), the findings suggest the importance of developing national AI education initiatives, standardized AI training programs, AI training certification systems, and clear guidelines for ethical AI use in higher education.

At the institutional level, universities should create AI use guidelines, integrate AI literacy and ethics into curricula, and provide AI training and certification opportunities for both students and instructors to strengthen responsible AI adoption. For university students, participating in AI training programs and engaging in self-learning activities can improve their understanding of AI capabilities, limitations, and appropriate applications, helping them use AI tools effectively, critically, and ethically in academic and future professional contexts. Students should also maintain academic integrity by verifying AI-generated information, preserving originality, and following institutional guidelines when using AI tools.

The study extends AI education beyond technological competence by highlighting the social and behavioral dimensions of responsible AI use. The findings emphasize the importance of integrating AI literacy, ethical awareness, academic integrity, and responsible decision-making into AI training programs in Cambodian higher education. However, several limitations should be acknowledged. First, the study was conducted at one private university and focused only on undergraduate students from the Faculty of Business Administration and Finance and Banking, which may limit the generalizability of the findings to students from other universities, academic disciplines, and educational levels.

Second, the study employed convenience sampling and a quantitative self-reported questionnaire, which may introduce potential response bias due to participants' subjective perceptions and reporting tendencies. Although Harman's single-factor test indicated no serious common method bias, future research may employ additional procedural remedies, such as temporal separation or multiple data sources, and statistical approaches to further validate the findings and reduce potential measurement bias. Additionally, the proposed model was developed using a limited number of indicators and analysed through PLS-SEM, which may restrict the comprehensive validation and comparison of the proposed relationships.

Future research should extend the current findings by collecting data from more diverse samples across multiple public and private universities, academic disciplines, and educational levels using more rigorous sampling approaches. Future studies may also incorporate additional constructs and measurement indicators to provide a more comprehensive explanation of ethical AI use among students. Moreover, longitudinal, experimental, or mixed-method research designs could provide deeper insights into how AI literacy and ethical AI practices develop over time. Finally, future research should consider integrating recent AI-related literature with foundational theoretical perspectives to strengthen the understanding of responsible AI adoption in higher education.

5. CONCLUSION

The primary objective of this study was to investigate the relationships among the AI training program, AI literacy, and ethical AI use among AI-trained undergraduate students in Cambodia. Despite the increasing adoption of AI in higher education, empirical evidence explaining how AI training experiences contribute to students' AI literacy and ethical AI use remains limited, particularly in developing countries. Grounded in Social Cognitive Theory, this study developed an integrated model to examine the effects of the AI training program on

AI literacy and ethical AI use, the influence of AI literacy on ethical AI use, and the mediating role of AI literacy in the relationship between the AI training program and ethical AI use.

The results revealed that all four proposed hypotheses were significantly supported. Specifically, the AI training program significantly enhanced AI literacy and ethical AI use, while AI literacy also demonstrated a significant positive effect on ethical AI use. Furthermore, AI literacy significantly mediated the relationship between the AI training program and ethical AI use, demonstrating that AI knowledge serves as a vital cognitive mechanism through which training experiences are translated into responsible AI practices. These findings highlight that AI training programs contribute not only to students' technical understanding but also to their ability to apply AI tools ethically and appropriately in academic contexts.

Overall, this study extends SCT by demonstrating how environmental factors, including the AI training program, cognitive capabilities, including AI literacy, and behavioural outcomes, involving ethical AI use, interact within the context of AI adoption among university students. The study provides empirical evidence from Cambodian higher education and highlights the significance of integrating AI literacy development with ethical considerations in AI training initiatives.

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DECLARATION OF AI USAGE

The author used Grammarly to improve the linguistic clarity of selected sections of the manuscript and consulted ChatGPT for explanations of statistical concepts and procedures related to PLS-SEM (e.g., measurement model assessment, f^2, Q^2, CR, AVE, HTMT, common method bias, bootstrapping, and structural model evaluation). All research design, data analysis, interpretation of findings, and conclusions presented in this manuscript are the author's original work and intellectual contribution.

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