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Ethical Awareness, Perceived Usefulness, and AI Literacy Predict University Students' Intentions to Use AI Tools

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ABSTRACT

Purpose – This study examines how ethical awareness and perceived usefulness shape university students' intentions to use artificial intelligence tools, and whether artificial intelligence literacy mediates these relationships in higher education.

Design/methods/approach – A quantitative cross-sectional survey was administered to 85 diploma and undergraduate students with prior experience using artificial intelligence for academic activities. The research model included perceived usefulness, ethical awareness, artificial intelligence literacy, and behavioral intention to use. Data were analyzed using partial least squares structural equation modeling with 5,000 bootstrapping resamples to evaluate measurement quality, test direct effects, and assess mediation.

Findings – Perceived usefulness significantly predicts behavioral intention to use artificial intelligence tools and also strengthens artificial intelligence literacy. Ethical awareness significantly increases artificial intelligence literacy but does not directly predict behavioral intention. Artificial intelligence literacy significantly predicts behavioral intention and mediates the effects of both perceived usefulness and ethical awareness on intention. These findings suggest that ethical awareness alone may increase caution unless supported by sufficient literacy that enables students to evaluate benefits, limitations, and risks of artificial intelligence tools.

Research implications/limitations – The cross-sectional design, purposive sampling, and a single-institution sample limit causal inference and generalizability. Future studies should use larger and more diverse samples and longitudinal designs.

Originality/value – This study provides empirical evidence that artificial intelligence literacy functions as a key mediating mechanism linking ethical awareness and perceived usefulness to artificial intelligence usage intention, informing responsible adoption strategies in higher education.

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INTRODUCTION

The development of Artificial Intelligence (AI) has brought about significant changes across various sectors, including higher education. AI is increasingly utilized as a decision support system, learning assistance tool, and means of enhancing efficiency and academic performance of students (L. Chen et al., 2020). Through its ability to process data, provide recommendations, and automate cognitive tasks, AI is perceived as capable of delivering substantial added value to the teaching and learning process, particularly in improving learning efficiency and the quality of students academic outcomes (F. Wang et al., 2023). However, despite its potential benefits, AI implementation raises various risks and challenges. Issues such as algorithmic bias, lack of transparency in decision-making processes, and threats to user data privacy have become serious concerns regarding the use of AI in academic environments (Chinta et al., 2025). These risks position AI as a technology that not only demands efficiency but also requires careful ethical and regulatory consideration (Memarian & Doleck, 2023; Wiese et al., 2025). Therefore, the adoption of AI cannot be understood merely as a technical decision but rather as a social phenomenon influenced by perceived benefits, ethical awareness, and users' cognitive capabilities.

In technology adoption studies, Perceived Usefulness (PU) is a central construct that explains the extent to which individuals believe that using a particular technology will enhance their performance. Based on the Technology Acceptance Model (TAM), PU is a primary predictor of technology usage intention (Achmadi et al., 2025). In the context of AI in higher education, students tend to adopt AI-based systems when they perceive tangible academic benefits, such as improved learning efficiency, higher-quality assignments, and enhanced learning outcomes(Ibrahim et al., 2024;Zhao et al., 2025). These findings confirm that PU remains a foundational factor in explaining user acceptance of AI. Nevertheless, the adoption of AI cannot be separated from ethical dimensions. The AI ethics literature emphasizes the importance of awareness of the principles of fairness, accountability, and transparency to ensure that AI usage does not generate harmful social consequences (Ghosh, 2025; Goreta et al., 2024; Kendal, 2022). Such ethical awareness influences how users evaluate the legitimacy, risks, and appropriateness of AI use in academic settings. Without adequate ethical understanding, users may employ AI uncritically, potentially leading to academic misconduct and systemic injustice.

In this regard, Artificial Intelligence Literacy (AIL) is regarded as an essential cognitive skill for responsible and informed AI usage(Brown et al., 2025). AIL enables individuals to understand how AI systems function, evaluate system outputs, and recognize algorithmic limitations and potential errors (Long & Magerko, 2020; Zhou et al., 2025). In higher education, AI literacy serves as a learning outcome and a prerequisite for critical, reflective, and ethical AI usage (Du et al., 2024). Research further indicates that ethical awareness and AI literacy are interrelated in shaping users evaluations of AI technologies. Individuals with higher AI literacy levels tend to be more capable of identifying biases and ethical risks, thereby avoiding blind reliance on AI systems (Ghosh, 2025). This suggests that perceptual, ethical, and cognitive aspects constitute interconnected dimensions that explain AI adoption behavior.

Although research on Perceived Usefulness (PU), AI ethics, and AI literacy continues to expand, most studies still examine these factors in isolation. Technology adoption research generally positions PU as the main predictor of usage intention, while AI ethics studies tend to be normative in nature and have not directly linked ethical considerations to actual usage behavior(Buhmann & Fieseler, 2021; Memarian & Doleck, 2023). Consequently, understanding AI adoption remains fragmented and fails to capture the complexity of interactions among variables, particularly in the context of the increasingly intensive use of AI in higher education.

Moreover, studies on AI literacy often conceptualize it as a learning outcome rather than a mechanism that explains how perceived usefulness and ethical awareness translate into technology usage intentions (Long & Magerko, 2020; Ng et al., 2021). This approach limits prior research in explaining the role of AI literacy as a bridge between technical understanding and users' normative evaluation. AI literacy can play a strategic role in connecting technical comprehension with ethical considerations in AI usage. Similarly, AI ethics research rarely operationalizes ethical awareness as an empirical variable influencing usage intention, leaving the relationship between ethical awareness and user behavior insufficiently tested (Ghosh, 2025). This limitation indicates that ethics are often treated as an abstract principle rather than as a psychological factor involved in users decision-making processes. This gap is increasingly relevant in higher education contexts, where students are both intensive AI users and future decision-makers. Without an integrated model that combines PU, ethical awareness, and AI literacy, previous studies have not been able to comprehensively explain AI usage intention (X. Chen et al., 2025; Zhao et al., 2025)

Based on these gaps, a research approach that integrates perceptual, ethical, and cognitive factors within a single conceptual framework is needed. Specifically, Artificial Intelligence literacy has the potential to function as a mediating mechanism that explains how perceived usefulness and ethical awareness influence AI usage intention. Literacy contributes to users self-efficacy, risk evaluation capabilities, and responsible technology adoption(Zeng et al., 2025). Therefore, examining AIL as a mediator enriches theoretical understanding and provides practical implications for developing AI literacy policies and programs in higher education.

In response to these gaps, this study aims to analyze the relationships among Perceived Usefulness (PU), Ethical Awareness (EA), artificial intelligence (AIL) literacy, and Behavioral Intention to Use AI (BI) in the context of AI usage among university students. Specifically, this study examined the direct effects of PU and EA on BI and the mediating role of AIL in these relationships. This approach is expected to provide a more comprehensive understanding of how cognitive, ethical, and perceptual factors interact to shape AI usage intention, while contributing to the advancement of technology acceptance theory and the practice of responsible AI literacy in higher education.

Based on the foregoing background, this study aims to address the following research questions:

RQ 1: Do Perceived Usefulness (PU) and Ethical Awareness (EA) have a significant effect on Artificial Intelligence Literacy (AIL)?

RQ 2: Do Perceived Usefulness (PU) and Ethical Awareness (EA) significantly affect the Behavioral Intention to Use AI (BI)?

RQ 3: Does Artificial Intelligence Literacy (AIL) significantly affect the Behavioral Intention to Use AI (BI)?

RQ 4: Does Artificial Intelligence Literacy (AIL) mediate the relationship between Perceived Usefulness (PU) and Ethical Awareness (EA) on Behavioral Intention to Use AI (BI)?

METHOD

Research Design

This study uses a quantitative approach with a cross-sectional design, in which data collection is conducted at a specific point in time to examine the relationship between ethical awareness, perceived usefulness, artificial intelligence literacy, and behavioral intention to use. This design was chosen because it is effective in describing the condition of respondents at the time of measurement and analyzing the influence of variables simultaneously in a single period. The cross-sectional approach is also suitable for student research because it is practical, efficient, and capable of providing a statistical picture of causal relationships based on the structural model used.

Participant

The participants in this study were 85 active diploma or undergraduate students who had used artificial intelligence (AI) technology at least once in a learning context, such as searching for information, preparing assignments, analyzing data, or using academic recommendation systems. Sample selection was conducted using purposive sampling techniques, considering that respondents must be active students and have experience using AI in academic activities, participate voluntarily, and be willing to fill out the questionnaire honestly and objectively. Based on demographic data, 36 students (42.5%) were male, and 49 students (57.5%) were female. The age distribution was dominated by 48 students (57.5%) aged 19 years, followed by 19 students (21.8%) aged 18 years, 14 students (16.1%) aged 20 years, and 4 students (4.6%) aged 21 years, indicating that the majority of participants were first- and second-year students who actively used AI technology in their academic activities.

Instrument

This research tool was compiled in the form of a questionnaire with a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) used to measure four main variables: *Perceived Usefulness* (PU), *Artificial Intelligence Literacy* (AIL), *Ethical Awareness* (EA), and *Behavioral Intent to Use* (BI) in *Artificial Intelligence* (AI)(Likert, 1932).

Table 1. Aspects and item description

Variable Name		Statement	References
Perceived Usefulness (PU)	PU1	The use of AI-based technology helps me complete academic tasks (such as research, presentations, or independent assignments) more efficiently.	(Alshammari & Babu, 2025)
	PU2	I feel that this technology facilitates my learning process.	
	PU3	AI-based technology provides tangible benefits in my learning activities, such as improving my understanding of the material or speeding up my work on assignments.	
	PU4	I can learn more effectively when utilizing this technology.	
	PU5	This technology is relevant to my academic needs.	
AI Literacy (AIL)	AIL1	I understand the basic workings of AI-based systems in providing information.	(Ng et al., 2021)
	AIL2	I can judge when the results of AI technology need to be re-examined.	
	AIL3	I am aware of the potential risks and biases that may arise from the use of AI.	
	AIL4	I am able to effectively utilize AI-based features to support learning.	
	AIL5	I know where to find information that can help me understand AI technology.	
Ethical Awareness (EA)	EA1	I recognize the importance of protecting data privacy when using digital technology.	(Chee et al., 2025)
	EA2	I consider the social impact when using AI-based technology, especially in terms of decision-making that can affect other people.	
	EA3	I feel it is necessary to be critical of the results provided by the automated system.	
	EA4	I strive to use technology responsibly in my learning activities.	
	EA5	I will not follow the advice of an automated system if I doubt its fairness.	
Behavioral Intention to Use (BI)	BI1	I intend to continue using AI-based technology in my learning process.	(C. Wang et al., 2024)
	BI2	I will try to use new technology that utilizes artificial intelligence.	
	BI3	I plan to recommend the use of AI-based technology to my colleagues.	
	BI4	I want to make AI technology part of my learning routine.	
	BI5	I am willing to improve my skills to become more proficient in using AI-based technology.	

Procedures

The research was conducted using an online questionnaire. Each respondent received an explanation of the research objectives and informed consent before completing the questionnaires. The stages of the procedure are shown in Figure 1.

Figure 1. Research Procedure

Data were collected by distributing online questionnaires to respondents who met the inclusion criteria. Researchers then checked the data for completeness to ensure that no items were missed and reviewed the data to detect unusual response patterns such as repetitive or inconsistent answers. Finally, the verified data were exported in CSV format for further analysis. The exported data were then analyzed descriptively using Jamovi software, including frequency distribution, percentages, and other respondent characteristics, followed by structural model testing using SmartPLS 4, which included evaluation of the outer model and inner model as needed for the study to test the relationship between variables and the mediating role according to the conceptual model. The results of the analysis were then presented in the form of tables, graphs, and model visualizations in accordance with PLS-SEM reporting standards, in which descriptive findings, construct validity, reliability, path coefficients, and mediation effects were systematically presented to support the interpretation and discussion of the research results.

Data Analysis

Data analysis in this study was conducted using SmartPLS 4 to test the validity, reliability, and relationships between the latent variables in the research model. The first stage involved evaluating the measurement model (outer model) by examining convergent validity using outer loading values and Average Variance Extracted (AVE), where indicators were declared valid if they had a loading above 0.70 and an AVE greater than 0.50(Henseler et al., 2015; Kock, 2015). Construct reliability was tested using Cronbach's Alpha and Composite Reliability, both of which must exceed a value of 0.70. In addition, discriminant validity was analyzed using the Fornell–Larcker Criterion to ensure that each construct had different characteristics from other constructs, making it suitable for use in structural model testing.

After the measurement model met all criteria, the analysis continued with structural model testing (inner model) using the bootstrapping method with 5,000 subsamples to obtain path coefficient values, t-statistics, and p-values. This test was used to assess the direct effects of EA and PU on BI and the effects of both on AIL. In addition, indirect effect analysis was conducted to identify the mediating role of AIL in the relationship between EA and PU on BI, while the total effect provided a comprehensive overview of the contribution of each variable to the AI usage intention. SmartPLS was chosen because the Partial Least Squares method is suitable for predictive models, does not require normally distributed data, and is effective for testing complex relationships and mediation in social research (Hair et al., 2014).

RESULTS AND DISCUSSION

Measurement of constructs

This study measures four main constructs, namely Ethical Awareness (EA), Perceived Usefulness (PU), Artificial Intelligence Literacy (AIL), and Behavioral Intention to Use (BI), with indicators adapted from technology adoption theory and AI literacy, which have been widely used in previous studies (Long & Magerko, 2020). All constructs were assessed using a 1–5 Likert scale, and the indicators were compiled in accordance with the principles of content validity, internal consistency, and concept representativeness, as recommended in the development of quantitative research instruments (Hair et al., 2014). The adjustment of indicators also considers the context of artificial intelligence use so that it can accurately describe students' perceptions, technical understanding, and intentions to use the technology. With accurate measurements, the structural model used in this study is expected to provide a comprehensive picture of the relationship between ethical awareness, perceived usefulness, AI literacy, and behavioral intention to use artificial intelligence in nursing. This approach is important to ensure that the evaluation of the influence between variables is based on valid and representative constructs in accordance with the latest conceptual references(Dwivedi et al., 2021).

Measurement Model Evaluation

The measurement model was evaluated using the PLS-SEM algorithm to examine the quality of the indicators (outer model) and to assess the reliability and validity of the constructs. Each construct in this study was measured using several indicators, such as PU1–PU5 for Perceived Usefulness, EA1–EA5 for Ethical Awareness, AIL1–AIL5 for Artificial Intelligence Literacy, and BI1–BI5 for Behavioral Intention to Use, which generally serve as measures of perceived usefulness, ethical awareness, AI literacy levels, and students' intention to use. Outer loading values were used to determine the contribution of each indicator in reflecting its construct, where the higher the loading value (ideally ≥ 0.70), the better the indicator represents the measured variable. Figure 2 visualizes the relationship between constructs and displays the performance of each indicator as a basis for assessing the validity and reliability of the model.

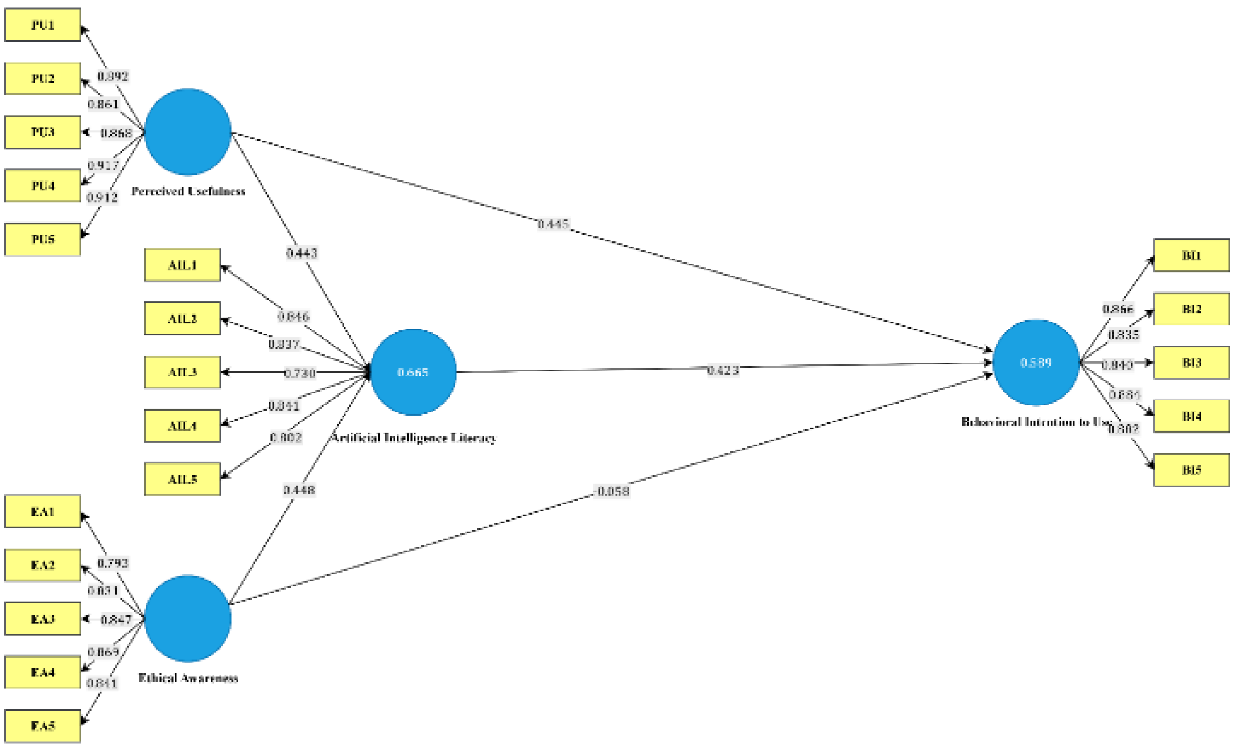

Figure 2. Outer Mode

Based on Figure 1, all indicators have outer loading values above 0.70, thus meeting the criteria for convergent validity, which indicates that each item adequately represents its construct (Guenther et al., 2023). The highest loading values were found in the Perceived Usefulness (PU) and Behavioral Intention (BI) constructs, indicating that both constructs have very strong measurement stability. Meanwhile, the uniformity of loading values in the Ethical Awareness (EA) and Artificial Intelligence Literacy (AIL) constructs indicates that respondents have consistent perceptions of ethical aspects and AI literacy, so that both variables are measured evenly across all the indicators. To ensure that measurement quality is met not only at the indicator level but also at the construct level, further reliability and validity evaluations were conducted. The results of these tests are presented in Table 2.

Table 2. reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Artificial Intelligence Literacy	0.871	0.879	0.906	0.660
Behavioral Intention to Use	0.913	0.916	0.935	0.742
Ethical Awareness	0.893	0.894	0.921	0.700

Perceived Usefulness	0.934	0.937	0.950	0.793

Source: Processed data, 2025

The high reliability values across all constructs indicate that each indicator has excellent internal consistency in measuring its respective variable. Composite Reliability (CR) and Cronbach's alpha values exceeding 0.90 in the Perceived Usefulness (PU) and Behavioral Intention (BI) constructs indicate very strong measurement stability and consistency of responses to each item (Mukhtar et al., 2022). In addition, all AVE values above the threshold of 0.50 confirm that the indicators can capture construct variance adequately and are not overly influenced by measurement error (Subhaktiyasa, 2024). To ensure that each construct was not only convergently valid but also had the ability to distinguish itself from other constructs, discriminant validity testing was conducted using the Fornell–Larcker Criterion. The results of the testing can be seen in Table 3, which shows whether the AVE root of each construct is above the correlation between constructs as a requirement for good discriminant validity.

Table 3. Fornell–Larcker Criterion

	Artificial Intelligence Literacy	Behavioral Intention to Use	Ethical Awareness	Perceived Usefulness
Artificial Intelligence Literacy	0.812	-	-	-
Behavioral Intention to Use	0.711	0.862	-	-
Ethical Awareness	0.747	0.558	0.837	-
Perceived Usefulness	0.745	0.721	0.674	0.890

Source: Processed data, 2025

Good discriminant validity was evident from the higher AVE root value compared to the correlation between constructs. This condition ensures that each construct measures a different concept and that there is no overlap between the variables (Lim, 2025). For example, AIL has an AVE root of 0.812, which is higher than its correlation with PU (0.622), which means that AI literacy is not merely influenced by perceived usefulness but is a conceptually independent construct. Thus, the measurement model met all validity and reliability criteria, making it suitable for structural model analysis.

Structure Model Evaluation

The structural model was analyzed to assess the relationships between the main variables and test the hypotheses formulated in this study. The testing was conducted by examining the significance value (p-value) for each relationship path, which could indicate whether the relationships between constructs, such as perceived usefulness, ethical awareness, Artificial Intelligence literacy, and behavioral intention to use, had a significant effect. In addition, the structural model can also be used to assess both direct and indirect (mediation) relationships between variables, so that the results offer an empirical understanding of the mechanism of influence between constructs in the conceptual framework of the study. The model structure visualization is shown in Figure 3, which shows the direction and weight of the relationships between the main variables.

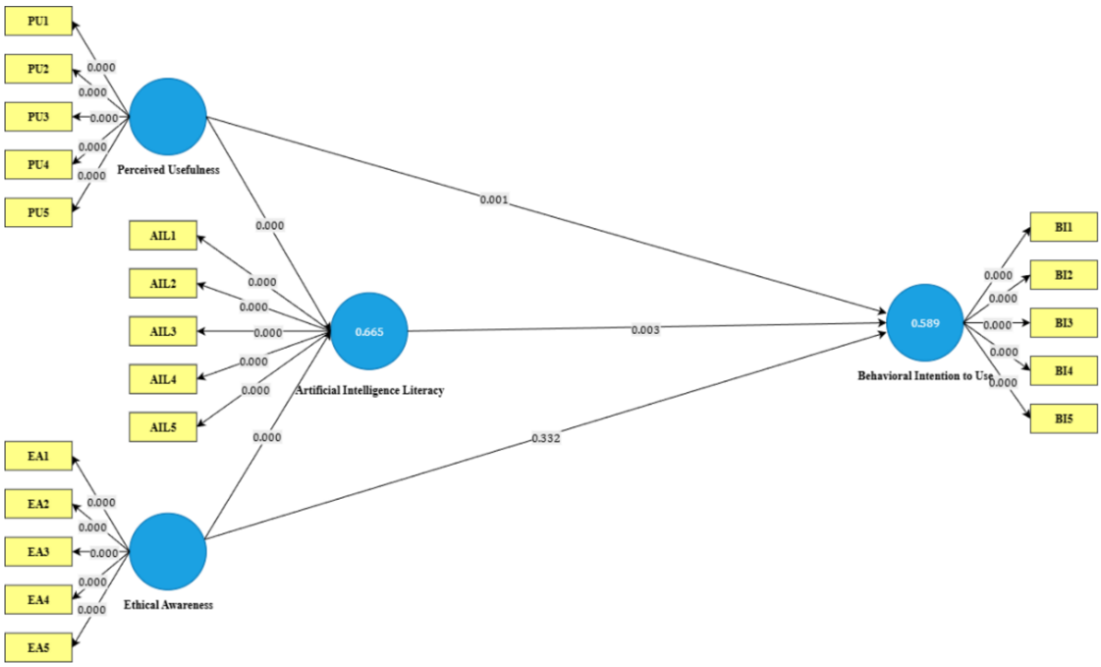

Figure 3. Structure model

Figure 3 displays the p-value for each relationship between variables, which shows that most paths have a high level of significance ($p < 0.05$), except for the relationship between Ethical Awareness (EA) and Behavioral Intention (BI), which is not significant ($p = 0.332$). lThese results confirm that most relationships in the model are stable and reliable (Gabriel et al., 2022). The findings show that Perceived Usefulness (PU) and Artificial Intelligence Literacy (AIL) play a more dominant role in shaping AI usage intentions than ethical awareness. Furthermore, EA and PU significantly affected AIL, indicating that AI literacy develops through a combination of perceived usefulness and sensitivity to ethical aspects. Among all paths, the relationship between PU and BI was the strongest, confirming that perceived usefulness is the main predictor of students' decisions to use AI. The consistency of these findings can be seen in more detail through the path coefficient values in Table 4.

Table 4. Hypotheses testing results

Hypotesis	Original sample (O)	T statistics	P values	Decision
H1 : Artificial Intelligence Literacy -> Behavioral Intention to Use	0.423	2.703	0.003	Significant
H2 : Ethical Awareness -> Artificial Intelligence Literacy	0.448	4.319	0.000	Significant
H3 : Ethical Awareness -> Behavioral Intention to Use	-0.058	0.436	0.332	Not Significant
H4 : Perceived Usefulness -> Artificial Intelligence Literacy	0.443	4.293	0.000	Significant
H5 : Perceived Usefulness -> Behavioral Intention to Use	0.445	3.233	0.001	Significant

Source: Processed data, 2025

The results in Table 4 show that most of the relationships between the variables in the model are significant and contribute strongly to the overall model structure. The variables Ethical Awareness (EA) and Perceived Usefulness (PU) were found to have a significant effect on Artificial Intelligence Literacy (AIL), illustrating that AI literacy is formed through a combination of ethical awareness and perceived usefulness. These findings are consistent with those of previous studies (Agustian et al., 2022). This emphasizes that perceived usefulness plays a major role in shaping students readiness and acceptance of AI technology. In addition, the path from PU to BI emerged as the strongest direct

influence in the model, in line with Achmadi et al. (2025b), which showed that PU is the main predictor of shaping the intention to use technology.
However, EA did not have a direct effect on BI, so its effect was only visible when mediated by AIL. Thus, AIL acts as an important link that strengthens the effects of EA and PU on BI, as further clarified by the indirect effects shown in Table 5.

Table 5. Indirect effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Ethical Awareness -> Artificial Intelligence Literacy -> Behavioral Intention to Use	0.190	0.195	0.078	2.418	0.008
Perceived Usefulness -> Artificial Intelligence Literacy -> Behavioral Intention to Use	0.187	0.201	0.094	1.991	0.023

Source: Processed data, 2025

As shown in Table 5, AIL is a significant mediator for both independent variables. AI literacy serves as a bridge that transforms ethical perceptions and benefits of AI into usage intentions (Brown et al., 2025). Without literacy, users may not feel confident using AI, even if they have ethical awareness or see the benefits of AI.

Discussion

The results of this study indicate that Artificial Intelligence Literacy (AIL) plays a central role in this research model as a mediator between Ethical Awareness (EA), Perceived Usefulness (PU), and Behavioral Intention to Use (BI) (Ng et al., 2021). This study confirms that increased ethical awareness and perceived usefulness are not sufficient to drive behavioral intention to use AI literacy, which is necessary for users to be able to assess the benefits and risks of technology more critically and responsibly (Nurhaliza, 2025). EA significantly affected AIL but did not directly influence BI, indicating that ethical components tend to generate caution and moral reflection rather than spontaneous technology adoption behavior (Kendal, 2022). This phenomenon is relevant to the findings of Du et al. (2024), where understanding privacy, fairness, and ethical risks actually suppresses interest in adoption if it is not accompanied by adequate technological literacy, so that EA acts as an ethical barrier that requires users to be careful before making decisions on the use of AI.
New ethical awareness has a positive effect on usage behavior when individuals have sufficient technical competence or AI literacy (Nurhaliza, 2025). AI literacy has been proven to improve users' ability to manage risks, understand the limitations of algorithmic models, and use AI technology responsibly and measurably (Ng et al., 2021). Improvements in AIL enable EA to function indirectly in strengthening BI, making literacy a bridge so that ethical influence is truly felt empirically in technology adoption decisions (Bogdadi et al., 2025). Perceived Usefulness (PU) emerged as the strongest predictor of BI, both directly and indirectly through literacy (Sari et al., 2025). These findings support the Technology Acceptance Model (TAM), which consistently places perceived usefulness as the main driver of technology behavior intention(Ng et al., 2021). Individuals who view AI as an effective solution for improving efficiency or convenience will be more enthusiastic about adopting and learning AI. Research Ibrahim et al. (2024) also emphasizes that PU not only influences intent, but also increases motivation to learn about technology, thereby encouraging increased AI literacy among users.
In addition, the mediating role of AIL is very strong in this model (Ng et al., 2021). Improved technical understanding has been shown to bridges perceptual and ethical factors with actual behavior (Zeng et al., 2025). AI literacy not only increases confidence and a sense of control over technology but also provides confidence in assessing the benefits and risks of its use more accurately (Bećirović et al., 2025). These literacy skills strengthen the influence of EA and PU on BI, making strategies to improve digital competence and conceptual understanding of AI among students very important for building ethical and productive usage behavior (Nurhaliza, 2025). This study reinforces the view that AI

adoption is not based solely on perceptions of usefulness but also on deep cognitive understanding and ethical considerations (Sari et al., 2025). The combination of PU, EA, and AIL forms a more mature decision-making framework in which individuals thoroughly consider the benefits, technical understanding, and ethical consequences before adopting AI (Aswan, 2025).

Based on the findings of this study, Artificial Intelligence Literacy (AIL) functions as a cognitive mechanism that bridges perceived usefulness and ethical awareness with behavioral intention to use AI. These findings indicate that technology adoption approaches that emphasize either perceived benefits or ethical considerations in isolation are insufficient to comprehensively explain user behavior. The results also have strong practical relevance, particularly in the context of higher education. The study demonstrates that high ethical awareness does not automatically lead to a stronger intention to use AI and may instead result in a more cautious stance when not supported by adequate technical understanding. Therefore, higher education institutions need to develop learning strategies that not only instill ethical values but also systematically enhance students AI literacy, enabling them to utilize AI technologies effectively and responsibly.

Furthermore, the findings of this study make a significant contribution to the literature on technology adoption and artificial intelligence (AI) literacy. This study empirically confirms the role of AI literacy as a key mediating variable linking ethical awareness and perceived usefulness to the behavioral intention to use AI. By demonstrating that ethical awareness does not exert a direct effect on usage intention, this study offers a novel perspective in which ethics functions as a reflective mechanism that requires literacy support to positively influence technology adoption behavior. This study enriches the current understanding of the dynamic interplay among ethics, cognition, and behavior in the context of AI use within academic settings.

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CONCLUSION

This study confirms that perceived usefulness is the strongest driver of university students' intentions to use artificial intelligence tools in academic contexts. Ethical awareness does not directly increase intention; instead, it operates through artificial intelligence literacy. Artificial intelligence literacy functions as a pivotal mechanism that translates both perceived academic benefits and ethical sensitivity into informed and responsible usage intentions. These findings indicate that higher education policies should not treat ethics training as a stand-alone intervention. Institutions should integrate ethics with structured artificial intelligence literacy development that strengthens students' ability to understand system limitations, evaluate outputs critically, and manage academic risks. Methodologically, the results should be interpreted cautiously due to the cross-sectional design, purposive sampling, and limited sample size within a single institution. Future research is recommended to apply longitudinal or experimental designs, include additional determinants such as trust, perceived risk, and institutional governance, and test the model across disciplines and institutions to improve external validity and explain intention formation more comprehensively.

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AUTHOR CONTRIBUTION STATEMENT

MS conceptualized the study, developed the research framework, and drafted the manuscript. ET contributed to instrument development, data collection, and data cleaning. AD performed the statistical analysis using partial least squares structural equation modeling and supported interpretation of results. DJ, SM provided theoretical guidance, validated the methodology, and contributed to manuscript revision. All authors reviewed, revised, and approved the final manuscript and agreed to be accountable for all aspects of the work.

AI DISCLOSURE STATEMENT

The authors declare that generative AI tools were used solely to support language editing, clarity, and readability during manuscript preparation. AI tools were not used to generate research ideas, design the study, collect data, conduct statistical analysis, interpret results, or draw conclusions. All AI-assisted text was reviewed and edited by the authors, who take full responsibility for the accuracy, originality, and integrity of the manuscript.

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