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AI Literacy Meets Ethics: Critical Appraisal's Mediating Role in Shaping Ethical Awareness in Higher Education

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Abstract

As artificial intelligence increasingly permeates higher education systems worldwide, developing students' ethical awareness has become essential for responsible AI implementation. This study seeks to examine the connections between technical understanding, applied knowledge, and critical appraisal in shaping ethical awareness within the context of AI literacy. The study utilizes a quantitative method, applying Partial Least Squares Structural Equation Modeling (PLS-SEM) to data gathered from 322 university students. The findings indicate that technical understanding has a direct favorable influence of 0.180 (p = 0.001) on ethical awareness, while applied knowledge demonstrates a stronger impact of 0.467 (p = 0.000). Critical appraisal serves as a significant complementary partial mediator, with indirect path coefficients of 0.083 (p = 0.014) for technical understanding and 0.155 (p = 0.007) for applied knowledge, strengthening their relationships with ethical awareness. This study concludes that AI literacy educational programs should not only emphasize technical and applied knowledge but also foster critical appraisal skills to promote ethical AI usage.

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INTRODUCTION

Artificial intelligence (AI) has become a pivotal driver of transformation across multiple sectors, notably in education. In higher education, the integration of AI has attracted significant scholarly attention due to its potential to improve institutional performance and support academic advancement (Alenezi, 2023). AI implementation in universities enables innovation in both teaching and learning processes, offering enhanced educational services and personalized learning experiences for students and instructors (Popescu et al., 2023). Among its many applications, AI facilitates curriculum customization, generates intelligent recommendations for learning materials, and provides predictive analytics to increase instructional efficiency (Mohamed, 2023). Moreover, AI supports educational quality by automating tasks such as assignment completion, problem-solving, and assessment (Mudinillah et al., 2023).

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AI is not only changing the way learning is conducted, but is also key in equipping students with the skills and competencies needed to compete in the increasingly digital and technology-based world of work of the future (Rožman et al., 2023). The integration of AI in higher education not only helps improve operational efficiency but also enriches students' learning experience by providing material tailored to individual needs and providing faster and more precise feedback (Akavova et al., 2023). Therefore, it is crucial to make sure that students have an adequate understanding of how this technology works. This is where the role of AI literacy becomes essential, equipping students with the skills and knowledge necessary to not only use AI effectively but also understand the ethical and social implications of its use (Grosseck et al., 2023).

AI literacy encompasses competencies required by AI technology users, including knowledge and understanding of AI, application of AI knowledge, evaluation and creation of AI, and adherence to AI ethics (Ng et al., 2021). Research has emphasized the significance of these competencies in utilizing AI effectively. First and foremost, technical understanding refers to the foundational knowledge necessary for interacting with AI systems. It includes a comprehensive grasp of data structures, computational thinking, and AI techniques, which are essential for evaluating the capabilities and limitations of the AI (Burgsteiner et al., 2016; Kandlhofer et al., 2016). For example, studies indicate that technical understanding plays a critical role in enabling individuals to make informed decisions to determine whether specific AI tools align with their needs. Therefore, a deep understanding of AI's technical background can enhance an individual's ethical awareness. This study will explore the direct influence of technical understanding on ethical awareness in AI usage.

Furthermore, Technical understanding enables individuals to recognize the distinction between general AI and narrow AI, expanding their awareness of AI's potential applications across various contexts, particularly in solving real-world problems (Morandini et al., 2023). Applied knowledge refers to the capacity to implement AI principles in practical situations. It combines theoretical understanding and practical experience to effectively apply AI-based solutions (Druga et al., 2019). Applied knowledge helps, identifying AI-supported applications in daily life or assessing whether a problem can be addressed using AI methods demonstrates the importance of applied knowledge. This competence also enhances the ability to determine when and how to rely on AI, ensuring its optimal and responsible use (Eisbach, 2023). Existing research highlights the importance of applied knowledge in empowering individuals to leverage AI technologies effectively (Druga et al., 2019; Long & Magerko, 2020). Practical experiences with AI are shown to improve problem-solving abilities and facilitate the integration of AI solutions into diverse contexts. Therefore, daily use of AI can increase an individual's ethical awareness, as it helps them understand when AI should be used and when it should be avoided. In this study, applied knowledge is seen as a factor that can enhance ethical awareness.

To effectively navigate and apply AI technologies, it is not enough to simply possess applied knowledge and technical understanding; evaluating AI is essential to process the information and make informed decisions. Evaluating AI refers to assessing AI systems from a higher-order thinking perspective, enabling individuals to analyze their validity, reliability, and ethical implications (Burden, 2024). This competence allows individuals to question AI's intelligence, reliability, and societal impact, ensuring a balanced and ethical approach to AI usage (Lee et al., 2023; Long & Magerko, 2020). Research shows that critical appraisal is essential for fostering ethical decision-making, empowering users to evaluate AI technologies critically, prevent over-reliance, and address potential risks (Nuraini et al., 2021; Styve et al., 2024). Lastly, and most importantly, AI Ethics, which involves understanding and applying ethical principles in AI usage, has gained significant attention due to the potential societal implications of the AI (Ansari, 2023). It stands out as the most crucial competency because it directly addresses social issues, such as the potential for AI to reinforce procrastination in completing assignments or the risk of reducing critical thinking skills in students who rely too heavily on AI tools (Ahmad et al., 2023).

However, while each of these competencies has been extensively studied, particularly in the context of decision-making skills using AI, a gap still exists in comprehending how they interact specifically and how they influence an individual's ethical awareness. One area that has received limited attention is the role of Critical Appraisal as a mediating variable that may shape the relationship between Technical Understanding, Applied Knowledge, on Ethical Awareness. This raises the question: does the ability to critically evaluate AI technologies increase the likelihood that individuals with strong technical knowledge and practical experience in AI will also exhibit higher ethical awareness, and is technical understanding and hands-on experience sufficient to ensure ethical AI use?

Traditional mediation tests, such as the (Baron & Kenny, 1986) approach, have been widely used, but recent studies (Hayes & Scharkow, 2013) have highlighted limitations in this method. In response, (Hair et al., 2021) integrated perspectives from (Zhao et al., 2010) earlier research on mediation analysis are used to develop a more comprehensive classification of mediation types. This study will employ Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the connections between these competencies, exploring how technical understanding, applied knowledge, and critical appraisal interact to influence ethical awareness. By examining this interplay, the research aims to offer new insights into how these competencies contribute to promoting ethical and responsible AI utilization. This research will offer new theoretical perspectives to the AI literature, particularly in understanding how individuals can use AI ethically and responsibly in practice.

METHOD

This study employed a quantitative research design for both data collection and analysis, focusing on numerical data to systematically examine phenomena and relationships among variables (Creswell, 2008). A cross-sectional approach was used, in which data were collected through surveys at a single point in time to analyze inter-variable relationships (Wang & Cheng, 2020). Purposive sampling was applied to select students who had actively used AI tools in their learning. Participants were categorized as "active users" if they consistently utilized platforms such as ChatGPT, Grammarly, QuillBot, or similar generative AI tools for academic tasks, including writing, problem-solving, coding, or conceptual exploration. This criterion ensured that respondents had relevant AI experience, allowing for a more meaningful investigation of the relationship between AI competence and ethical awareness (Campbell et al., 2020). The sample size was determined based on the PLS-SEM Rule of Thumb, which recommends at least ten participants per indicator used in the model (Hair et al., 2019). The participants were undergraduate students from Makassar State University. Ethical approval was secured, and all participants provided informed consent before completing the questionnaire.

The survey tool is composed of Likert scale items, designed to assess the latent variables in the study. The model features four latent variables, each evaluated on a 1-5 scale, where 1 indicates "strongly disagree," 3 stands for "neutral," and 5 signifies "strongly agree."(Norman, 2010). All latent variable measures were adopted from previous research that had developed and validated these scales. The three variables; Applied Knowledge, Technical Understanding, and Critical Appraisal were adopted from (Laupichler et al., 2023), while the Ethical Awareness variable was adopted from (Krügel et al., 2022) as detailed in Table 1.

Table 1. The instrument of AI Literacy on Ethical Awareness

Aspect	Item	Statement
Technical Understanding	TU1	I can elucidate the procedures of training, validating, and testing machine learning models.
	TU2	I can elucidate the connection between deep learning and machine learning.
	TU3	I can distinguish between rule-based systems and machine learning systems.
	TU4	I can elucidate the decision-making processes of AI systems.
	TU5	I can offer a fundamental elucidation of the mechanics of reinforcement learning in the context of machine learning.
	TU6	I can differentiate between general (or strong) AI and narrow (or weak) AI.
	TU7	I can elucidate how sensors assist computers in collecting data for AI applications.
	TU8	I am capable of defining an artificial neural network.
	TU9	I can elucidate the fundamental principles of machine learning.

Aspect	Item	Statement
	TU10	I can elucidate the distinction between unsupervised learning and alternative machine learning methodologies.
	TU11	I am capable of elucidating the concept of explainable AI.
	TU12	I can elucidate how certain AI systems engage with and react to their surroundings.
	TU13	I am capable of elucidating the concept of big data.
	TU14	I may evaluate the realistic representation of AI in media, such as films or video games, in relation to contemporary AI capabilities.
Critical Appraisal	CA1	I can elucidate the importance of data privacy in the development and utilization of AI technologies.
	CA2	I can elucidate the importance of data security in the development and application of AI.
	CA3	I can recognize the ethical dilemmas associated with AI.
	CA4	I can delineate the potential threats involved with the use of AI technologies.
	CA5	I acknowledge the constraints of artificial intelligence.
	CA6	I may delineate legal concerns that may emerge from the utilization of AI.
	CA7	I can analyze the potential effects of AI on individuals and society.
	CA8	I can elucidate the significance of human participation in the advancement of AI systems.
	CA9	I can elucidate the significance of data in the creation and implementation of AI.
	CA10	I am capable of defining artificial intelligence.
Applied Knowledge	AK1	I can present tangible instances from my personal or professional experiences involving interactions with AI.
	AK2	I can provide instances of AI-enhanced technology in actual applications.
	AK3	I can ascertain if the technologies I utilize integrate AI.
	AK4	I can assess the appropriateness of AI-based solutions for an issue in my domain.
	AK5	I can recognize instances of AI-enhanced natural language processing and understanding apps.
	AK6	I can elucidate the reasons behind the recent prominence of AI.
	AK7	I am capable of objectively evaluating the influence of AI applications in a minimum of one academic discipline.
Ethical Awareness	EA1	I can evaluate the societal implications of utilizing AI.
	EA2	I can incorporate ethical considerations while determining the use of data produced by AI.
	EA3	I am capable of assessing AI applications from an ethical perspective.
	EA4	I can elucidate the significance of ethics in the development and application of AI.
	EA5	I can elucidate the necessity of oversight and regulation to guarantee ethical AI techniques.
	EA6	I can examine the ethical implications of employing AI in decision-making, particularly in sensitive domains such as healthcare and law.
	EA7	I can contemplate the future of human-AI interactions and the significance of ethics in influencing these connections.

Data Analysis

Data analysis was performed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique (Agusnaya et al., 2024; Rauf et al., 2024), with SmartPLS version 3.3.3 software, to examine the connections between the components of AI Literacy and the mediating role of critical appraisal. Initially, the measurement model was assessed for construct validity and reliability using the PLS algorithm, followed by an evaluation of the structural model to examine direct connections between exogenous and endogenous variables, using the Bootstrapping algorithm (Hair, 2017; Hair et al., 2021).

In this research, Critical Appraisal was considered the mediator, with Technical Understanding and Applied Knowledge serving as independent variables, and Ethical Awareness as the dependent variable. To precisely capture the mediating effect, it is essential to identify the type of mediation involved. This study utilizes (Hair et al., 2021) integrated framework, which combines insights from (Zhao et al., 2010) and earlier research on mediation analysis, offering a more comprehensive classification of mediation types. Accordingly, the analysis of mediation types must be carried out systematically and rigorously, as depicted in Figure 1.

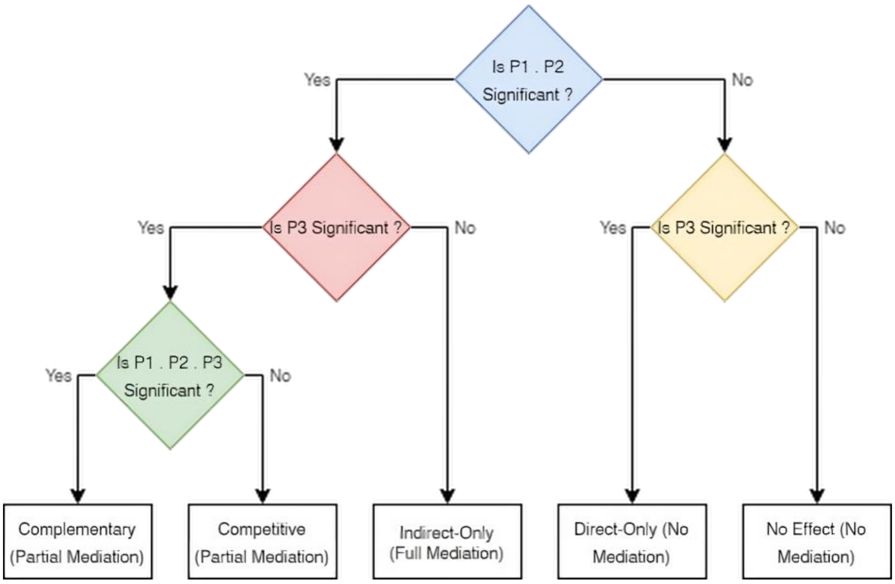

Figure 1. Mediating Analysis Procedure (Hair et al., 2021)

The research constructs involved in exploring the effects of Technical Understanding can be seen in Figure 2, Applied Knowledge on Ethical Awareness (H1, H2). Technical Understanding and Applied Knowledge on Critical Appraisal (H4, H5), and subsequently, on Ethical Awareness in the context of AI literacy (H3). The figure depicts the hypothesized relationships among these constructs, demonstrating how each component contributes to the development of ethical awareness through the mediating role of critical appraisal (H6, H7).

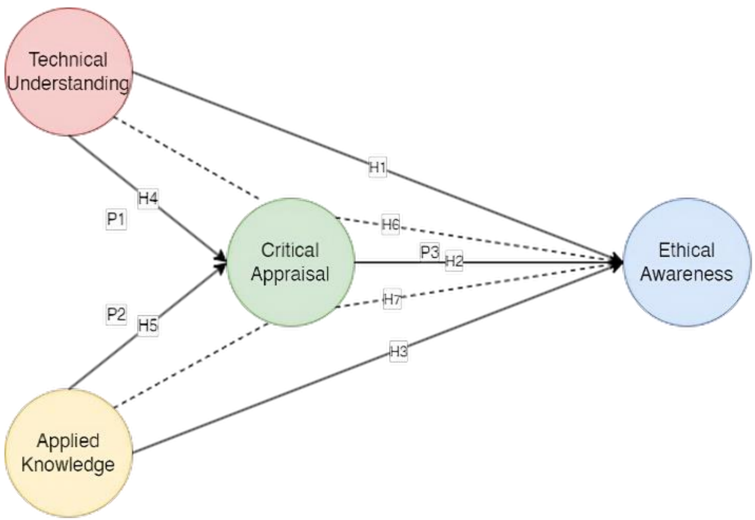

Figure 2. Research Construct

Figure 2 shows the research constructs for understanding hypotheses:
1. Hypothesis 1: Technical Understanding significantly and positively influences Ethical Awareness.
2. Hypothesis 2: Applied Knowledge significantly and positively influences Ethical Awareness.
3. Hypothesis 3: Critical Appraisal significantly and positively influences Ethical Awareness.
4. Hypothesis 4: Technical Understanding significantly and positively impacts Critical Appraisal.
5. Hypothesis 5: Applied Knowledge significantly and positively impacts Critical Appraisal.
6. Hypothesis 6: Critical Appraisal plays a significant and positive role in mediating the relationship between Technical Understanding and Ethical Awareness.
7. Hypothesis 7: Critical Appraisal plays a significant and positive role in mediating the relationship between Applied Knowledge and Ethical Awareness.

RESULTS AND DISCUSSION

The total number of respondents is 322, all of whom are students at Makassar State University. The distribution of respondents by gender shows a majority of female respondents, with 192 females (59.6%) and 130 males (40.4%). The largest percentage of respondents is 19 years old (45.7%), with the smallest percentage being 22 years old (1.2%).

Evaluation of the measurement model

The measurement model was initially evaluated using the PLS algorithm to assess its reliability and validity. In structural equation modeling, reliability consists of two key components: item reliability and construct reliability. Item reliability was assessed through outer loading values, with a recommended threshold of 0.7; however, values above 0.5 may still be accepted if convergent validity is not compromised (Hair & Alamer, 2022). Construct reliability was evaluated using Cronbach's Alpha and composite reliability, both requiring minimum values of 0.7 (Hair et al., 2021). Additionally, Dillon-Goldstein's rho was used to assess internal consistency and further support model reliability (Hair et al., 2021). For validity, both convergent and discriminant validity were examined. Convergent validity was measured using the Average Variance Extracted (AVE), with 0.5 set as the minimum acceptable threshold (Hair & Alamer, 2022).

Table 2. Reliability and Validity Results

Construct	Items	Outer Loadings	Cronbach's Alpha	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technical Understanding	TU1	0.787	0.953	0.955	0.958	0.623
	TU2	0.804				
	TU3	0.796				
	TU4	0.783				
	TU5	0.768				
	TU6	0.746				
	TU7	0.838				
	TU8	0.775				
	TU9	0.823				
	TU10	0.808				
	TU11	0.768				
	TU12	0.768				
	TU13	0.800				
	TU14	0.779				
Critical Appraisal	CA1	0.745	0.922	0.923	0.934	0.588
	CA2	0.790				
	CA3	0.737				
	CA4	0.722				

Construct	Items	Outer Loadings	Cronbach's Alpha	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
	CA5	0.781				
	CA6	0.753				
	CA7	0.770				
	CA8	0.856				
	CA9	0.758				
	CA10	0.751				
Applied Knowledge	AK1	0.775	0.889	0.892	0.913	0.601
	AK2	0.812				
	AK3	0.810				
	AK4	0.711				
	AK5	0.740				
	AK6	0.843				
	AK7	0.726				
Ethical Awareness	EA1	0.757	0.897	0.901	0.919	0.618
	EA2	0.722				
	EA3	0.776				
	EA4	0.831				
	EA5	0.809				
	EA6	0.779				
	EA7	0.825				

The results presented in Table 2 confirm that all items within each construct have outer loading values above 0.7, indicating strong item reliability. This is further reinforced by the values of Cronbach's Alpha, composite reliability, and Dillon-Goldstein's rho, all of which exceed the threshold of 0.7, supporting the constructs' internal consistency (Hair, 2006). In terms of convergent validity, the Average Variance Extracted (AVE) for each construct is above 0.5, demonstrating that the indicators sufficiently explain the variance within their respective constructs (Hair & Alamer, 2022). Together, these findings affirm that the measurement model meets the criteria for both reliability and convergent validity.

To evaluate discriminant validity, two methods were used: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio (Fornell & Larcker, 1981; Hair et al., 2019). The Fornell-Larcker test confirms discriminant validity when the square root of the AVE for each construct is shown on the diagonal of the correlation matrix and is greater than its correlations with other constructs in the same row and column (Hilkenmeier et al., 2020), as displayed in Table 3. Additionally, the HTMT ratio, which provides a stricter assessment, indicates adequate discriminant validity when all values remain below 0.85, as shown in Table 4 (Henseler et al., 2015).

Table 3. Fornel Lacker

	AK	CA	EA	TU
AK	0.775			
CA	0.755	0.767		
EA	0.764	0.731	0.786	
TU	0.538	0.628	0.598	0.789

As shown in Table 3, all diagonal values representing the square roots of the Average Variance Extracted (AVE) are consistently higher than the inter-construct correlation coefficients in the corresponding rows and columns. This finding indicates that each construct shares greater variance with its indicators than with other constructs, thereby meeting the Fornell-Larcker criterion for discriminant validity. This criterion is widely applied to confirm that each construct is empirically distinct from the others in the model. To strengthen this assessment, the Heterotrait-Monotrait (HTMT) ratio was also employed. This method offers a more stringent evaluation by measuring the degree of similarity between constructs. According to Henseler et al. (2015), HTMT, values should ideally remain at or below 0.85 to ensure sufficient discriminant separation. As presented in Table 4, all HTMT values met this threshold, further affirming that the constructs in this study demonstrate satisfactory discriminant validity.

Table 4. Heterotrait-monotrait Ratio (HTMT)

	AK	CA	EA	TU
AK				
CA	0.829			
EA	0.847	0.798		
TU	0.571	0.661	0.638	

As shown in Table 4, all HTMT values are below the recommended threshold of 0.85, which signifies that the constructs are not excessively correlated with one another. This implies that each construct maintains its conceptual distinctiveness and does not overlap significantly with others in the model. When combined with the Fornell-Larcker results, these findings provide strong evidence that the measurement model satisfies the criteria for discriminant validity, confirming that the constructs are empirically distinct and appropriately measured.

Evaluation of the Structural Model

For structural measurement, the Bootstrapping Algorithm is utilized to assess the statistical significance of parameter estimates in testing both direct and indirect effects (see Table 5). This process evaluates metrics such as Path Coefficients and P-Values to test the hypotheses. Path coefficients, which quantify the influence between constructs, are deemed positive when their values exceed zero (Hair et al., 2021). P-values, which indicate probability, are considered statistically significant at the 5% level if they are 0.03, signifying the relevance of the coefficient (Hair, 2017).

Table 5. Direct Effect Result

Hypotheses	Path Hypotheses	Path Coefficient (β)	P-Value	Decisions
H1	TU->EA	0.180	0.001	Supported
H2	AK->EA	0.467	0.000	Supported
H3	CA->EA	0.265	0.003	Supported
H4	TU-> CA	0.312	0.000	Supported
H5	AK-> CA	0.586	0.000	Supported

Based on the data presented, all hypothesized pathways show positive and significant results. The findings indicate that Technical Understanding (TU) is positively and significantly related to Ethical Awareness (EA) ($\beta = 0.180$, $p = 0.001$), and Applied Knowledge (AK) also has a positive and significant influence on Ethical Awareness ($\beta = 0.467$, $p = 0.000$). Additionally, Critical Appraisal (CA) is found to be positively and significantly associated with Ethical Awareness ($\beta = 0.265$, $p = 0.003$). Furthermore, Technical Understanding significantly impacts Critical Appraisal ($\beta = 0.312$, $p = 0.000$), and Applied Knowledge also enhances Critical Appraisal ($\beta = 0.586$, $p = 0.000$).

Table 6. Indirect Effect Result

Hypotheses	Path Hypotheses	Path Coefficient (β)	P-Value	Decisions
H6	TU->CA->EA	0.083	0.014	Supported
H7	AK->CA->EA	0.155	0.007	Supported

Based on the results from the indirect effects table 6, both hypotheses indicate significant mediation effects, suggesting that Critical Appraisal (CA) acts as a mediating variable in the relationships between Technical Understanding (TU) and Ethical Awareness (EA), as well as Applied Knowledge (AK) and Ethical Awareness. For H6 (TU -> CA -> EA), the path coefficient is

0.083 with a p value = 0.014, indicating that Critical Appraisal partially mediates the relationship between Technical Understanding and Ethical Awareness. Similarly, H7 (AK -> CA -> EA) shows a path coefficient of 0.155 with a p value = 0.007, demonstrating that Critical Appraisal also partially mediates the relationship between Applied Knowledge and Ethical Awareness.

Given the significance and positive direction of these indirect effects, the mediation type in both cases is best described as complementary partial mediation. This occurs because both the direct effects (from Technical Understanding and Applied Knowledge to Ethical Awareness) and the indirect effects (through Critical Appraisal) are significant and point in the same direction, as illustrated in Figure 3.

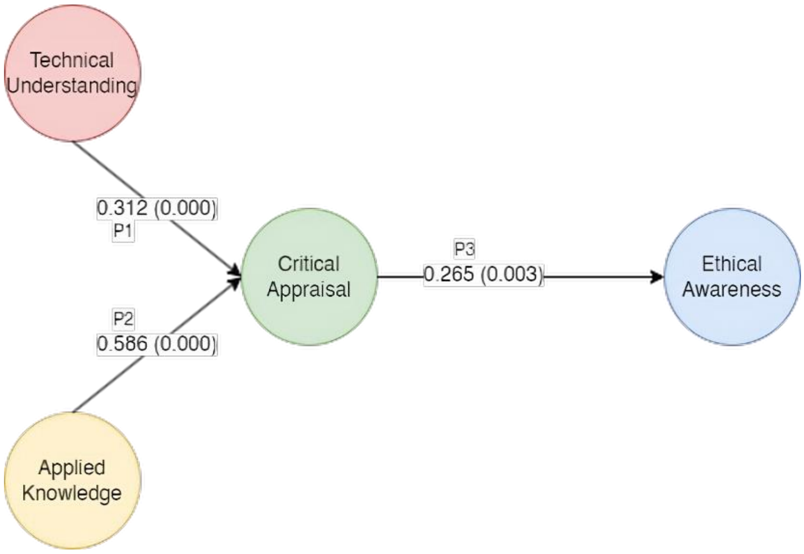

Figure 3. Mediation Type Result

The findings of this study provide robust evidence supporting the positive and significant relationships between Technical Understanding (TU), Applied Knowledge (AK), and Critical Appraisal (CA) with Ethical Awareness (EA) in the context of AI literacy. Each of these relationships aligns with previous research, reinforcing the theoretical foundations of this study and providing new insights into the dynamics between these competencies.

TU-EA

First, the significant positive relationship between Technical Understanding (TU) and Ethical Awareness (EA) (β = 0.180, p = 0.001) suggests that a solid grasp of AI's technical aspects is crucial for developing ethical awareness among students. This understanding forms the basis for making informed decisions about AI use, particularly in contexts where ethical considerations are paramount. Previous literature has shown that developers with a strong technical background have a direct correlation with their ability to make ethical decisions (Pant et al., 2024). This technical foundation enables students to critically assess the ethical implications of AI systems, ensuring that their use aligns with societal values and norms. Furthermore, a previous study suggests that while technical aspects are important, their successful adoption and integration depend significantly on how well they resonate with the users' social practices and ethical considerations (Sloane & Zakrzewski, 2022).

AK-EA

Similarly, the strong positive influence of Applied Knowledge (AK) on Ethical Awareness (EA) (β = 0.467, p = 0.000) underscores the importance of practical experience in shaping ethical considerations. By applying AI knowledge in practical scenarios, students are more likely to encounter ethical challenges firsthand, prompting them to consider the ethical dimensions of their actions (Brusseau, 2023). This experiential learning process is crucial for fostering a deep and nuanced understanding of AI ethics. Previous studies have demonstrated that understanding AI's capability to perform various tasks accurately can help individuals make better-informed decisions about when to rely on and how to effectively utilize AI(Eisbach, 2023). This aligns with the findings of this research, which reveal a positive and significant impact of Applied Knowledge on Ethical Awareness in students' AI usage, emphasizing the importance of practical AI knowledge in fostering responsible and ethical decision-making among learners.

CA-EA

The positive association between Critical Appraisal (CA) and Ethical Awareness (EA) (β = 0.265, p = 0.003) further emphasizes the role of critical thinking in ethical decision-making. Critical Appraisal involves questioning the validity, reliability, and biases inherent in AI systems, which is key to developing a responsible and ethical approach to AI usage. This competency ensures that students do not merely accept AI outputs at face value but instead engage in thoughtful analysis of the ethical implications. For example, Integrating Generative AI tools in programming courses enhances critical thinking, enabling students to discern AI's implications for ethical decision-making regarding risks and benefits (Styve et al., 2024). Another study highlights how critical thinking enables students to analyze ethical dilemmas effectively, thereby facilitating informed and ethical decision-making (Nuraini et al., 2021).

TU-CA

This study also highlights the significant influence of Technical Understanding on Critical Appraisal (β = 0.312, p = 0.000), suggesting that a strong technical background enhances one's ability to critically evaluate situations. This finding is consistent with the work of Federico, who found that individuals with a deeper understanding of technical aspects are better equipped to engage in critical thinking, as they can draw on a richer knowledge base to evaluate the complexities of a situation (Federico et al., 2022). Another study also shows that technical literacy goes beyond just knowing how to use technology; it involves understanding its limitations and the appropriate contexts for its use, which is crucial for critical assessment (Chin-Yee et al., 2023).

AK-CA

Moreover, the significant effect of Applied Knowledge on Critical Appraisal (β = 0.586, p = 0.000) supports the idea that hands-on experience contributes to better critical evaluation. As suggested by Halpern, applied learning provides the context and experience necessary for meaningful reflection and critique (Yadav et al., 2024). This relationship underscores the importance of integrating practical experiences into educational and professional development programs to enhance both critical appraisal and ethical awareness. Another study also found that Hands-on technology-based activities enhance learning by reinforcing cognitive knowledge and retention, suggesting they can increase critical thinking skills through practical application and experiential learning.(Fior et al., 2024).

TU-CA-EA and AK-CA-EA

The mediation analysis demonstrates that Critical Appraisal plays a significant mediating role between Technical Understanding and Ethical Awareness (β = 0.083, p = 0.014), as well as between Applied Knowledge and Ethical Awareness (β = 0.155, p = 0.007). These results suggest that the relationship between technical and applied AI knowledge and ethical awareness is significantly strengthened when individuals possess strong critical appraisal skills. Specifically, the observed complementary partial mediation highlights that while Technical Understanding and Applied Knowledge contribute independently to Ethical Awareness, the incorporation of critical thinking amplifies these effects. This finding underscores the importance of fostering critical appraisal skills, as they enable individuals to contextualize and evaluate AI technologies beyond their immediate functionalities, considering broader ethical implications. For instance, the ability to critically evaluate AI systems allows individuals to identify and mitigate potential risks, such as over-reliance on AI, biased outputs, or the erosion of independent critical thinking skills (Ahmad et al., 2023; Ranard et al., 2024).

The interplay between the relationships among Technical Understanding, Applied Knowledge, and Critical Appraisal offers an in-depth insight into how these factors collectively contribute to Ethical Awareness. Technical Understanding provides the foundational knowledge required to grasp the inner workings and limitations of AI technologies. When this technical base is complemented by Applied Knowledge or practical engagement with AI systems, individuals are better equipped to evaluate real-world scenarios and applications. Critical Appraisal serves as the bridging factor that synthesizes these elements, enabling individuals to reflect on the ethical dimensions of AI use. For instance, an individual with strong technical expertise (TU) might recognize the capabilities of an AI system, while practical experience (AK) informs them about its functional applications. However, without Critical Appraisal, the ability to question biases, foresee potential ethical dilemmas, and evaluate consequences might remain underdeveloped.

By mediating the relationships between both Technical Understanding and Ethical Awareness, as well as Applied Knowledge and Ethical Awareness, Critical Appraisal enhances the ethical decision-making process. This interplay suggests that ethical awareness in AI usage is not solely dependent on technical expertise or hands-on experience but is significantly elevated through the integration of critical thinking. This comprehensive perspective reinforces the notion that knowledge, practice, and reflection are all necessary for fostering ethically responsible AI engagement, supporting prior findings that practical scenarios and critical reflection deepen ethical understanding in professional practice (Conlon & Zandvoort, 2011). Furthermore, critical thinking bridges the gap between knowledge and ethical action, empowering individuals to make well-informed, ethically sound decisions regarding AI technologies (Pesic, 2007).

LIMITATIONS

This study presents specific limitations. Initially, the sample was limited to university students, which might not adequately reflect the varied perspectives of the wider population regarding AI literacy and ethical awareness. The random sampling conducted within this particular demographic yields important insights; however, it also constrains the extent to which these findings can be generalized to other populations, including professionals or those with varying educational backgrounds. Secondly, although the study identifies important connections between the variables, it overlooks potential moderating factors like gender, cultural background, or previous experience with AI. This limitation suggests that subsequent investigations ought to consider these factors to enhance comprehension of how these relationships may vary among different populations. Ultimately, reliance on self-reported data can introduce bias. Future investigations could integrate more objective measures or mixed-method approaches to enhance the validation of the findings.

CONCLUSION

To conclude, this research highlights the interconnected nature of AI literacy competencies and their combined influence on ethical awareness. The results provide strong evidence that Technical Understanding (TU), Applied Knowledge (AK), and Critical Appraisal (CA) play a crucial role in shaping Ethical Awareness (EA) within the realm of AI literacy, especially among university students. Educational programs should prioritize not just improving students' technical and applied AI knowledge, but also emphasize the cultivation of critical appraisal skills. By fostering these competencies, educators can ensure that students are skilled in AI technologies while being mindful of their ethical implications, ultimately shaping responsible and ethical AI practitioners. This study contributes to the growing body of work on AI literacy and provides practical recommendations for creating educational programs that emphasize ethical awareness. Future AI literacy programs can utilize these findings to develop more comprehensive strategies that enhance technical skills and promote ethical responsibility in AI applications across various environments.

Future studies ought to explore the potential variations in the relationships among technical understanding, applied knowledge, critical appraisal, and ethical awareness across different genders. This could yield valuable insights for customizing AI literacy programs to address the specific needs of various demographic groups. Longitudinal studies could investigate the progression of students' technical and applied knowledge, alongside their critical appraisal skills, over time and how these factors shape their ethical awareness, ultimately aiding in the creation of more effective AI literacy curricula. Furthermore, integrating objective assessments, like task-based evaluations of ethical decision-making in AI contexts, with self-reported data could improve the reliability of findings and offer a more precise gauge of ethical awareness. Increasing the sample size and diversity may enhance the comprehension of the elements that affect ethical awareness in AI. The proposed directions for future inquiry will enhance the groundwork laid by this study and facilitate the development of inclusive AI literacy initiatives that emphasize ethical considerations. The identified areas for additional investigation will enhance the groundwork laid by this study and aid in the creation of more inclusive and effective AI literacy initiatives that emphasize ethical awareness.

AUTHOR CONTRIBUTIONS

PAS led the research design, data analysis, revision, and interpretation of the study. MMF contributed to data collection and provided critical reviews of the manuscript for intellectual depth and clarity. FA played a key role in reviewing the manuscript. KPP supported the research by assisting with data collection and manuscript review. FA focused on reviewing the manuscript to enhance its overall quality.

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