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AI Literacy, Technical Skills, and Ethical Awareness in Predicting Students' Learning Performance

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Abstract

The increasing integration of AI systems into various sectors of the economy has also raised ethical concerns. Even as education in AI has developed to ensure that learners have the appropriate technical skills, the existing systems have failed to address the issue of ethics. As a way of addressing the problem, the current study aims at investigating learning about AI literacy and ethical reasoning. The author in this research applied the Partial Least Squares Structural Equation Modeling (PLS-SEM), from a questionnaire consisting of 400 university students (conducted of informatics and computer engineering department) to examine the relevance of AI literacy (AI-DAIB theories/basics), technical skills (TS), learning performance (LPER and EAI as moderating effect on AI perception (AIP). The findings found interesting result that AI literacy and technical skills have significant effects on learning performance and the moderating effect of AI ethics also increases the added value. This study indicates the need for a wider framework of all educational activities focusing on the development of technical skills, AI literacy and (semi)AI ethics to respond effectively to gaps in both development and moral responsibility of AI technologies.

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INTRODUCTION

The inclusion of artificial intelligence (AI) in educational paradigms has emerged as a significant factor, especially with the continued evolution of technology, which has significantly impacted society (Alkhawaja et al., 2025; Tolentino et al., 2024). There is a need to ensure technical competency in artificial intelligence, along with a need to ensure a good understanding of the ethical implications associated with it, especially since it has become an integral part of everyday life (Black et al., 2023). There is an urgent need to ensure that individuals become proficient in the subject matter of artificial intelligence, including the ethical considerations associated with it, to create well-informed citizens who are capable of recognizing the ethical considerations associated with it (Du et al., 2024). This includes not only the ability to understand, evaluate, and use artificial intelligence, but also critical thinking, problem-solving, and social assessment of the implications of artificial intelligence (Babashahi et al., 2024; Zhang et al., 2023). Nevertheless, it has been noted in the existing literature that proficiency in artificial intelligence is not only about technical

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competency but also about assisting learners in dealing with the moral implications associated with it (Ng et al., 2020).

Ethical issues surrounding AI decision-making, data privacy, and potential bias in AI programs require curricula to also address social responsibility (Kim et al., 2021). This further emphasizes the need to incorporate ethical considerations into AI literacy education, which has been neglected in the current education system (Casal-Otero et al., 2023). Furthermore, studies suggest that teachers must be taught about AI literacy and ethics so they can educate their students about the same, further emphasizing the need for better teacher training (Chaaban et al., 2024; Zhao et al., 2022).

Investigating the role of ethics in AI education, and, more specifically, how AI literacy and technical skills impact learning performance, indicates that there is a research gap that needs to be addressed. Specifically, it is important to note that there is a research gap related to the fact that AI literacy must be considered from multiple dimensions, including its cognitive, technical, ethical, and behavioral aspects (Biagini, 2024). This is supported by Zhang et al. (2022), which suggests the need for AI education to include the ethical, social, and occupational aspects of AI, thereby showing the need for AI education to cover the various aspects of AI. Furthermore, the existing literature points to the need for conducting empirical studies on the practical application of AI literacy in the context of learning environments. For instance, the studies conducted by Wang & Wang (2024). For example, Smith et al. (2023) highlight the lack of empirical studies on the practical application of AI literacy, particularly in non-technical contexts. Such an argument is also supported by Komasawa & Yokohira (2023), which highlights the need for the development of learning frameworks that incorporate AI literacy, data science, and ethical considerations. Moreover, the relationship between the application of AI literacy and educators' willingness to teach the same also needs to be explored. For instance, Ibrahim (2024) argues that the need of the hour is to train educators, which would improve their proficiency in the application of AI, which in turn would improve their willingness to teach the same to their students.

Besides, the fast pace at which AI technology is advancing serves to emphasize the need for continued research into the ethical implications of AI technology. Studies on the impact of ethics education in AI technology among secondary school students have demonstrated the need to integrate ethics into AI literacy education to prevent ethical violations related to AI technology. Therefore, this suggests that educational strategies should focus not only on developing students' knowledge and skills, but also on developing their ethical knowledge and critical thinking skills. Despite the growing body of research on AI literacy and its use in education, several limitations remain. For example, most studies on AI literacy and the application of AI in education focus on curriculum development, student conceptions, and perceptions of AI technology. However, studies employing analytical methods to examine the association of AI technology competency and attitudes with educational outcomes are scarce.

This study's main goal is to bridge this knowledge gap by studying the incorporation of ethical reasoning and considerations in the design of AI literacy courses, along with how awareness of ethical issues may moderate increased technical competency and student learning outcomes. With this study, we hope to give insight into the creation of a framework accommodating technological innovation paired with ethical responsibility.

METHOD

A quantitative research approach was used in this study to examine the impact of various dimensions (technical competence and ethical understanding) of artificial intelligence literacy on student learning performance. A survey method was used to collect the necessary data, with the study population consisting of university students with an understanding of AI-related concepts. Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied for evaluating the structural links among diverse latent variables, given its capacity for complex model testing with various constructs and possible moderation results. (Cheah et al., 2021; Hair et al., 2021). Both the measurement model and the structural relationships between the proposed variables were examined.

Participants

The study participants consisted of 400 students from Universitas Negeri Makassar, specifically from the Computer Engineering and Informatics study program and the Computer Engineering Education study program. In this study, the sampling method used was purposive sampling, in which the participants are selected based on their knowledge and experience in the field of artificial intelligence technology (Mohd Dzin & Lay, 2021). The questionnaire used in the study was conducted at a single point in time. All the participants volunteered to join the study, with the consent of the participants obtained before the questionnaire was submitted to the researchers. Confidentiality of the participants was ensured by anonymizing the participants' identities before the study was conducted (Dyer & Kim, 2021).

Demography

The sample was predominantly 19 years old, followed by 18 and 20 years old, with the remainder consisting of individuals aged 20 years and above. In terms of the sample's gender composition, the results indicate that 44.2% were male, while the remaining 55.8% were female. In terms of academic level, the sample consisted predominantly of second-semester students, followed by fourth-semester students, with the remainder consisting of individuals in other semesters. The study showed that the majority of the population consisted of people studying in the Informatics Education and Computer Engineering study programs, followed by the Computer Engineering study program, with the least number of people studying in other study programs.

Instrument Development

A structured questionnaire was designed after a thorough review of the literature to collect data. The questionnaire was developed to measure five constructs related to AI learning, which include ‘AI Definitions and Basics (DAIB)’, ‘AI Perceptions (AIP)’, ' Technical Skills (TS)’, ’AI Ethics (EAI)', and finally ’Learning Performance (LPER)’. The tool was pre-tested by experts to ensure clarity, reliability, and consistency before its administration.

The measurement elements used to measure each construct are shown in Table 1. Each variable is associated with four elements in five dimensions of knowledge, perception, technical skills, ethics, and learning performance relevant to the context of artificial intelligence learning.

Table 1. Aspects and Item Description

Aspect	Item	Statement
Definitions and AI Basics	DAIB1	AI has a clear understanding for me.
	DAIB2	I understand the basics of AI development.
	DAIB3	My knowledge of AI covers a wide range of applications in daily life.
	DAIB4	I can identify the differences between AI and conventional computer concepts.
	DAIB5	I understand basic concepts such as machine learning and artificial neural networks.
AI Perceptions	AIP1	The field of work may positively be impacted by AI.
	AIP2	I have no doubt that the advancement of AI will improve civilization.
	AIP3	AI is more effective than humans at solving complicated issues.
	AIP4	I think that in order to avoid unfavorable outcomes, the advancement of AI should be properly watched.
	AIP5	While AI is progressing very rapidly, I have some reservations about its effect on human jobs.
Technical Skills	TS1	I feel comfortable using various algorithms in AI development.
	TS2	My understanding of programming languages supports the development of AI solutions.
	TS3	I can implement machine learning models in practical projects.
	TS4	My understanding of deep learning concepts is adequate for practical applications.
	TS5	I am able to evaluate and improve the performance of AI models effectively.

Aspect	Item	Statement
Ethics AI	EAI1	I have an impactful understanding of why we prioritize ethical development and application of AI.
	EAI2	I believe the development of AI systems should be transparent to promote accountability.
	EAI3	I believe that the use of AI should be fair and equitable.
	EAI4	I believe that AI should not be used to manipulate information or public opinion.
	EAI5	I understand that data security aspects are very important in the development and use of AI.
Learning Performance	LPER1	I feel that the current curriculum is sufficient to teach AI skills.
	LPER2	I feel that assessments in AI reflect my true understanding of the material.
	LPER3	I believe that projects and assignments involving the use of AI can improve my understanding.
	LPER4	I feel that support from lecturers or instructors is essential to improving my AI skills.
	LPER5	I believe that the use of online resources and reference books can help improve my understanding of AI.

Data Collection

Data was collected using a purpose-designed questionnaire, which was created using a combination of literature review, expert validation, and pilot testing to ensure ease of understanding, reliability, and overall effectiveness. The tool was used to assess various aspects of AI-related understanding, perception, technical ability, ethics, and learning performance, etc. The tool used a 4-point Likert scale, ranging from 'strongly disagree' to 'strongly agree.' After collecting the data, it was coded, and using a combination of quantitative techniques, including descriptive analysis and partial least squares structural equation modeling (PLS-SEM), the relationships between the data sets were explored, along with contextual understanding (Huang, 2021; Jebb et al., 2021).

Measurement of Variables

This study comprises five latent variables, each assessed through five structured items, bringing the total number of measurement indicators to 25. All indicators were measured using a 4-point Likert scale ranging from 1 (“strongly disagree”) to 4 (“strongly agree”), which allows for nuanced yet efficient differentiation of respondent agreement levels while minimizing neutral bias. The constructs measured in this study are defined as follows:

The assessment of Learning Performance through indicators such as the appropriateness of AI assessments, belief in AI projects improving understanding, instructor support, and the usefulness of resources is well-documented. Research indicates that instructional support and appropriate resources significantly enhance technology learning outcomes. For instance, a study by emphasizes the role of formative indicators in measuring educational outcomes, which aligns with the indicators used in this study (Marelić et al., 2024). This performance is assessed through four indicators: the appropriateness of AI assessments to the actual understanding of the material (LPER2), the belief that AI projects and assignments improve understanding (LPER3), the importance of instructor support in improving AI skills (LPER4), and the usefulness of online resources and reference books in deepening AI understanding (LPER5). Previous research shows that instructional support and the use of appropriate resources play a major role in successful technology learning (Lawless & Pellegrino, 2007; Pala, 2023).

AI Definitions and Basics evaluates students' basic understanding of AI concepts. Indicators include basic understanding of AI development (DAIB2), knowledge of AI applications in daily life (DAIB3), ability to distinguish AI from conventional computer concepts (DAIB4), and mastery of basic concepts such as machine learning and neural networks (DAIB5). This understanding is crucial in building a strong foundation in AI education, as well as fostering flexibility in accommodating new technologies (Kim et al., 2017).

AI Perceptions is an instrument that measures students' perceptions or attitudes towards the influence or capability of artificial intelligence. The items are as follows: the belief that AI has a positive influence in the workplace (AIP1), the belief that AI brings positive changes in society (AIP2), the efficiency of AI in addressing complex issues in comparison to human beings (AIP3), and the belief in the need to closely monitor the development of AI to avoid adverse consequences (AIP4). Positive perceptions of AI could help students develop more interest in learning technology-related subjects (Bisdas et al., 2021; Grassini, 2023; Teng et al., 2022).

Technical Skills measure the students' competence in the creation and deployment of artificial intelligence applications. The parameters include: knowledge of various artificial intelligence algorithms (TS1); knowledge of the programming languages used in artificial intelligence creation (TS2); capacity to integrate machine learning in the projects (TS3); knowledge of concepts in deep learning in the creation of applications (TS4); and the capacity to improve the performance of artificial intelligence models (TS5). Good technical skills are essential in the execution of artificial intelligence in educational projects (Alkhawaja et al., 2025).

The AI ethics will act as a moderating variable that either increases or decreases the strength of the link that the independent variable shares with the dependent variable. In this case, the awareness of AI ethics will increase the strength of the link that basic AI understanding (DAIB) shares with learning performance (LPER). This is because AI ethics is crucial in the development of AI technology, as well as in the learning process (Kapp et al., 2022; Vimalanathan et al., 2022).

Data Analysis

The data obtained were analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). This method is appropriate for examining the complex associations among latent constructs and can deal with predictive research models in a robust manner. Assessing the measurement model (i.e., validity and reliability tests) and structural model to analyze proposed linkages between variables included in the study (Cheah et al., 2021; Hair et al., 2021; Huang, 2021).

RESULTS AND DISCUSSION

Measurement Model

Composite Mode A

Documenting individual items' reliability, discriminant validity, convergent validity, and construct reliability of the composite measurement model in mode A (Judijanto et al., 2023). It was analyzed with the loading factors shown in Figure 1.

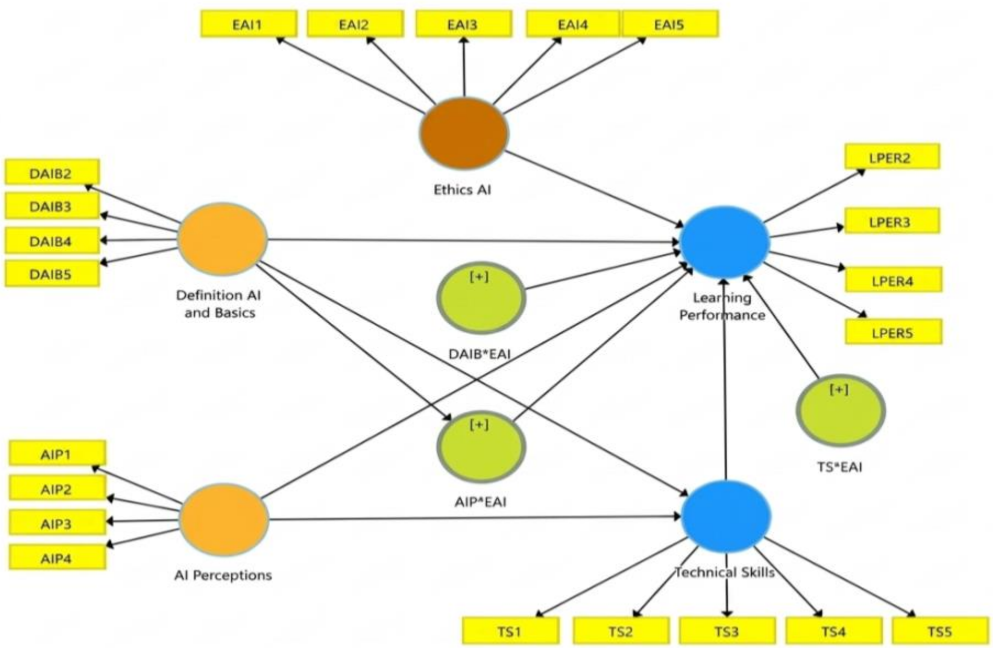

Figure 1. Proposed Model

The next step after visualising the proposed model in Figure 1 is to evaluate the reliability and validity of the research instruments through the following means: (1) evaluating individual item reliability; (2) assessing the discriminant validity; (3) assessing the convergent validity, and (4) determining the construct reliability. Different statistics are used in this analysis in order to establish that the measurement model meets the criteria that have been specified, such as Cronbach's Alpha, rho_A, and Composite Reliability (Hair et al., 2021). More accurate measures for internal consistency are composite reliability. PLS-SEM is compatible with multi-item evaluative indicators with various loadings (Amiruddin et al., 2023).

The results of the validity and reliability tests of the tested models are presented in Table 2, which provides an overview of the extent to which the research instruments are reliable in measuring the established constructs.

Table 2. Validity and Reliability Measurement

Constructs and Interaction Terms	Cronbach's Alpha	Rho_A	Composite Reliability	AVE
AI Perceptions	0.822	0.832	0.883	0.654
AIP*EAI	1.000	1.000	1.000	1.000
DAIB*EAI	1.000	1.000	1.000	1.000
Definition AI and Basics	0.799	0.803	0.869	0.623
Ethics AI	0.895	0.895	0.922	0.704
Learning Performance	0.832	0.857	0.889	0.669
TS*EAI	1.000	1.000	1.000	1.000
Technical Skills	0.869	0.880	0.904	0.653

Convergent validity is analyzed to ensure that each indicator in a construct has a significant contribution to the concept being measured. This is tested by looking at the Average Variance Extracted (AVE) number, which shows how much of the variance can be attributed to the construct as opposed to measurement error (Tabet et al., 2019). The three primary metrics—Cronbach's alpha, Dijkstra-Henseler's rho coefficient, and composite reliability—all have a cutoff value of 0.7. Additionally, since each construct's AVE value was greater than 0.5, convergent validity was verified (Reyna-Castillo et al., 2022).

Table 2 presents the results of the validity and reliability measurements of the tested models. By looking at the values in the table, it can be determined whether the model meets the criteria set out in this study. Furthermore, to test discriminant validity, the Heterotrait-Monotrait correlation ratio (HTMT) was used (Cheung et al., 2024). The test results displayed in Table 3 show that all constructs meet the discriminant validity criteria, where the confidence interval does not include a zero value. This confirms that each variable in the model has a clear distinction from the others. Thus, the data analyzed in this measurement model confirm that all constructs used are reliable and valid (Cheah et al., 2021).

Table 3. Heterotrait-Monotrait-Ratio (HTMT)

Constructs	AIP	AIP*EAI	DAIB*EAI	DAIB	EAI	LPER	TS*EAI	TS
AIP	-							
AIP*EAI	0.3226	-						
DAIB*EAI	0.3708	0.2764	-					
DAIB	0.3829	0.3684	0.4639	-				
EAI	0.5296	0.3826	0.5684	0.3684	-			
LPER	0.3621	0.2222	0.4884	0.2222	0.4884	-		
TS*EAI	0.3226	0.2226	0.3708	0.3708	0.2226	0.3226	-	
TS	0.2701	0.2062	0.0778	0.3226	0.2701	0.2701	0.2701	-

The Heterotrait-Monotrait Ratio (HTMT) was used to test Discriminant Validity. The results show that all of the constructs met the Discriminant Validity requirement, which means that each one is conceptually different from the others.

Composite Mode B

Collinearity between indicators, as well as the importance and applicability of external weights, were evaluated for the composite measurement model in mode B. Indicators with Variance Inflation Factor (VIF) values greater than three were initially removed in order to prevent multicollinearity issues. The other signs were kept for additional examination as they satisfied the suggested threshold (Nur'aini, & Hamzah, 2023; Hsu et al., 2023). Next, the relevance of the weights was examined, as illustrated in Figure 2, focusing on the relevance of indicators in constructing latent variables.

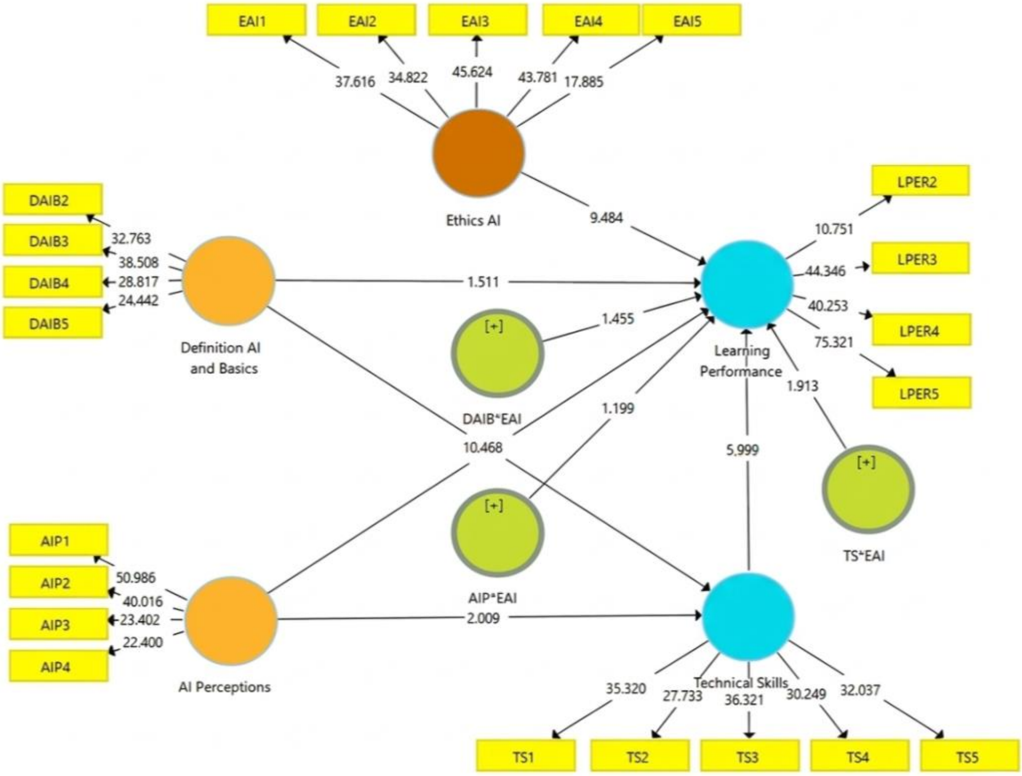

Figure 2. SEM Model Using PLS-SEM

After establishing the measurement model, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to analyze the structural relationships among the constructs.

Structural Model and Hypotheses Testing

H1: AI Definitions and Basics-Learning Performance

The positive link between AI Definitions and Basics and Learning Performance suggests that students' performance in learning is positively affected by their basic knowledge of AI. This is in accordance with Oh (2023)the assertion that students' understanding of AI concepts is crucial in their adaptability to new technologies. The high value of the link could also be attributed to the fact that AI is increasingly used in various fields, making it crucial for students to have basic knowledge in the field to help them understand the more complex concepts. In addition, students with basic knowledge in AI may not face challenges in their learning process, thus improving their performance.

H2: AI Definitions and Basics - Technical Skills

The positive influence of the basics of AI on technical skills indicates the logical progression from theoretical understanding to practical application. Such an outcome confirms the proposition that Liao et al. (2020), which suggests that the proper understanding of theories enables the acquisition of advanced technical skills. The positive influence of the basics of AI on technical skills indicates the logical progression from theory to practice.

H3: AI Perceptions - Learning Performance

Students whose perceptions of artificial intelligence were positive had better academic performance, which is consistent with Katsuyama et al. (2020) when they stressed the motivational aspect of positive perceptions of technology. This is also in conformity with the self-determination theory, whereby intrinsic motivational power, through the promotion of positive attitudes, will enhance learning performance. The findings also suggest that the effect size is not solely based on perceptions when there is inadequate knowledge and skill in the field.

H4: AI Perceptions - Technical Skills

The role of perceptions of artificial intelligence in the development of technical skills implies that students with a positive perception of artificial intelligence are likely to develop the necessary skills since they are motivated to learn, thus improving their technical skills. This is in line with the findings of Babashahi et al. (2024) & Bellini et al. (2024), who indicated that positive attitudes towards technology encourage exploration and persistence in problem-solving activities.

H5: Technical Skills - Learning Performance

The positive relationship between technical skills and learning performance indicates that practical skills have an important impact on the academic performance of students. This finding supports the significance of practical competencies in academic achievement, as emphasized in the study conducted by Krisnandi (2023). The strength of this relationship may also indicate an increasing emphasis on practical skills in modern education, where practical projects are becoming an integral part of the assessment criteria.

Moderating Effects of AI Ethics

H6: AI Ethics Moderates AI Definitions and Basics - Learning Performance

The moderating role of AI ethics suggests that ethical awareness will strengthen the relationship between basic AI knowledge and learning performance. This is similar to the statement from Liu & Su (2024), that ethics will strengthen critical thinking and reflective learning. The significant effect could also imply that students who understand AI concepts from both technological and ethical perspectives will be able to apply their knowledge thoughtfully.

H7: AI Ethics Moderates AI Perceptions - Learning Performance

Although the moderating effect is considerable, it is not as pronounced as in H6. This suggests that while awareness of ethics positively moderates the effect of positive perceptions of AI, this effect is stronger when it is complemented by knowledge, as in H6. This finding supports the study Wang & Wang (2024), which suggested that ethics education promotes a deeper understanding of the social impact of technology and, in turn, indirectly improves academic performance.

H8: AI Ethics Does Not Significantly Moderate Technical Skills → Learning Performance

Contrary to expectations, AI ethics did not have a significant impact on this relationship. This suggests that the ability to apply technical skills in an academic setting may be guided more by procedural skills than by ethical skills. This is supported by Chaaban et al. (2024) which indicates that ethics have a limited impact on technical execution, especially in terms of hands-on skills, with cognition and perception being the main areas where ethics have an impact.

H9: Direct Effect of AI Ethics on Learning Performance

The direct and substantial impact of AI ethics on learning performance also highlights the importance of ethical literacy in the academic environment. According to the argument, Du et al. (2024) ethical literacy promotes critical thinking, decision-making, and reflective learning, all of which are important for academic achievement. Such an argument indicates that ethics must not be learned in isolation.

Overall, the findings indicate that cognitive and affective aspects of AI literacy are related to students' learning performance. In other words, basic knowledge of AI and positive perceptions of AI help students develop their AI skills, thereby improving their learning performance.

Furthermore, the inclusion of AI ethics was found to be an important factor that enhances the academic value of AI knowledge and perceptions.

LIMITATIONS

There are certain limitations associated with this study. The research sample was drawn from a single university; this restriction may limit the generalizability of the results to other populations, so future research will need to include individuals from multiple universities and diverse educational backgrounds to yield more generalizable findings. Second, because this is a cross-sectional study, it limits the ability to make causal claims about the relationships among the variables included in this study. More research is needed on the long-term impact of AI literacy and ethics education on student learning outcomes through longitudinal studies. Lastly, this study relied primarily on self-reported data from students' perceptions, which could affect the results due to response bias. Only qualitative research was used, and in addition, objective measures of this help to achieve more representative results regarding the benefits of AI literacy and ethics in education.

CONCLUSION

This study investigates the relationship between AI literacy, technical skills, and learning performance, with particular attention to the dimension of AI ethics within the construct of so-called AI literacy. The results after working on a project likely reflect that, first, experienced individuals with AI are already familiar with its definition and understand at least some basic concepts of the technology, and that this experience also surfaces stronger technical skills and strengthens their learning. Moreover, technical skills are an important factor in learning performance, underscoring the importance of practical skills in AI-related academic work. Additionally, the results reveal that AI ethics directly affects learning performance and serves as a moderator in the model, indicating the significance of AI ethics for learning outcomes and for the relationship among the variables in the model. In terms of practical implications, the study revealed the importance of AI literacy in improving learning performance and the role of AI ethics in promoting the understanding and application of AI knowledge in the educational context.

Thus, it is recommended that educators and policymakers promote AI literacy that includes understanding AI definitions and basics, fostering positive perceptions of AI, and developing technical skills. Furthermore, promoting AI ethics in AI literacy is likely to enhance students' understanding and application of AI knowledge in educational contexts and improve their learning outcomes in AI-related studies. Future studies should examine the promotion of AI ethics across different educational contexts and its effects on students' learning performance and technological skills. This is likely to promote the development of a comprehensive AI literacy framework in the future, given AI's increasing role in education.

AUTHOR CONTRIBUTIONS

The major contributions of DMJ and MMF were conceptualizing the study, developing the methodology, conducting the formal analysis, and leading the investigation. They were also responsible for providing resources for the study. In terms of manuscript development, SS and MMF contributed to drafting, which SS, SH, MY, SNW, ABK, and SA then reviewed. DMJ and MMF handled the visualization, while SS oversaw the entire process.

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