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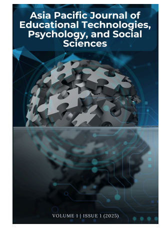

Research Article

The Nexus Between AI Literacy and Digital Literacy of Students in Region XI as Moderated by Sex

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Abstract

The disparity in knowledge between AI literacy and digital literacy among students in Region XI is hindering their ability to acquire crucial technology skills. The purpose of this study is to investigate the moderating effect of sex on the relationship between AI literacy and digital literacy. Using a quantitative, non-experimental research design, data were collected through stratified random sampling with surveys and analyzed via Partial Least Squares Structural Equation Modeling (PLS-SEM). Methodological validity was ensured through statistical tests, confirming high reliability for constructs such as AI learning (Cronbach's alpha = 0.913) and digital literacy (Cronbach's alpha = 0.966). The findings indicate that AI literacy significantly improves digital literacy, with a path coefficient of 0.523 and a significance level of $p < 0.001$. Self-efficacy (0.586, $p < 0.001$) and competency (0.612, $p < 0.001$) were identified as crucial mediators in this process. Additionally, AI literacy's influence on self-competency showed a strong positive relationship (path coefficient = 0.612, $p < 0.001$), emphasizing its role in shaping student competencies. However, the interaction effect of sex on AI literacy's influence on digital literacy was marginal (path coefficient = 0.218, $p = 0.063$). These findings underline the need to incorporate AI literacy into educational curricula. Integrating AI education can bridge knowledge gaps and enhance specific digital competencies, such as critical thinking and problem-solving. According to the study, activities focusing on artificial intelligence should be included in digital literacy programs to better prepare children for a technologically driven future.

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Introduction

Artificial intelligence (AI) literacy has become essential in today's education sector, given the expanding role of AI technologies in shaping learning environments, personalization, and overall academic outcomes (Long & Magerko, 2020; Ng et al., 2021). It encompasses not only the ability to understand and use AI tools but also the capacity to critically evaluate their applications and ethical implications, particularly within educational contexts (Obenza et al., 2024). In the Philippines, AI literacy is gaining recognition as education policies increasingly emphasize digital skills to prepare students for an AI-driven workforce (Estrellado, 2023). Moreover, these digital and AI capabilities allow students to work successfully with technology, augmenting creativity, critical thinking, and problem-solving (Eguchi, 2021; Druga et al., 2019).

Several initiatives have been implemented in Region XI to integrate AI technologies into educational settings, highlighting the need for AI literacy to enhance academic performance. Recent studies have indicated that acquiring AI-related skills can significantly improve students' communication and analytical capacities, making it a highly worthy area of emphasis (Kong et al., 2021; Lee et al., 2021). Additionally, the connection between AI literacy and broader digital literacy is critical for students to gain not just technological capabilities but also the cognitive abilities required to navigate the current digital environments (Canan Güngören et al., 2022; Balakrishnan & Dwivedi, 2021).

Despite the significant progress in promoting digital literacy, a notable research gap remains regarding the specific intersection of digital and AI literacy among the students in Region XI. While digital literacy focuses on essential technological competencies, AI literacy delves deeper into understanding AI's functionalities and ethical aspects (Ng et al., 2022; Juma, 2021). Cognitive engagement, or absorption, is particularly relevant in this context, as high engagement levels have enhanced students' digital competencies and their preparedness to use AI tools effectively (Canan Güngören et al., 2022). Studies show that students' learning outcomes related to artificial intelligence (AI) are greatly affected by cognitive absorption, which refers to an immersive engagement with technology (Balakrishnan & Dwivedi, 2021; Wang & Lu, 2023). Addressing this research gap is essential, particularly given that integrating AI and digital literacy could further support students in adapting to a highly technological academic and professional landscape (Yi & Park, 2021; Obenza-Tanudtanud & Obenza, 2024).

This study aims to investigate the link between AI literacy and digital literacy among Region XI students, emphasizing how these abilities interact and increase academic engagement. It focuses on the function of cognitive absorption in AI literacy, investigating how the students' degrees of interaction with AI technologies affect their total digital literacy. By addressing this gap, the study hopes to provide empirical data that can inform educational policy and teaching methods in Region XI. These findings are expected to help educators and policymakers shape a balanced development of AI and digital literacy abilities that are appropriate for modern educational contexts (Obenza et al., 2024; Eguchi, 2021).

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Theoretical Framework

This study highlights the connection between different types of literacy and how they improve people's technology skills through the Integrated Literacy Theory (ILT) framework. In Region XI, the inclusion of digital and AI literacy has significantly helped students become more adept with technology. According to ILT, digital literacy is essential because it provides students with the basic skills to navigate the digital world, think critically, and understand rules and regulations (Ng, 2012).

AI literacy is the ability to understand how AI systems work, how they process data, and how they make decisions, especially when it comes to ethical issues in AI technology (Long & Magerko, 2020). As the student builds ICT capability, there will be an expected development in their AI literacy skills that helps them address moral and critical issues related to AI technology. Consequently, educators utilize digital literacy as an effective tool to impart skills that enable students to interact responsibly with AI technologies. While students may be familiar with standard technology in the classroom, AI literacy enables them to critically assess and apply AI-based applications (Luckin et al., 2016).

The growing presence of AI-designed products makes it essential to include digital and AI literacy in curricula, which is also in line with global education trends and the ILT paradigm. Students become better at making smart decisions and using technology responsibly when they learn different types of literacy and see how knowledge is connected. ILT helps prepare them for the workforce by focusing on both basic skills and more advanced technical skills needed for specific careers (Goggin et al., 2019; Passey et al., 2018).

Digital literacy and artificial intelligence literacy are crucial components of student preparedness, as discussed in this article using an integrated learning theory (ILT) approach. The study examines how effectively students can navigate challenges in a rapidly evolving technological landscape. It highlights the importance of connecting different forms of literacy, which has significant implications for developing an innovative curriculum. This is essential to meet the technical skills and adaptability demands of the technology industry, as well as the needs of students

Materials and Methods

This study uses a quantitative and non-experimental approach, research design, in order to investigate the relationship between AI literacy and digital literacy among students in Region XI. In the definition given by Creswell and Creswell (2023), it was asserted that quantitative research design employs structured tools, such as surveys, in gathering data, enabling statistical measurements and analysis. Furthermore, in selecting participants, stratified random sampling was used to ensure the diversity and representation of the samples, which was then applied by grouping the participants based on their programs, year levels, and schools. This gives equal opportunities to individuals to present the results effectively, ensuring representation across various categories, guaranteeing fairness, and reducing bias (Iliyasu & Etikan, 2021; Taherdoost, 2016).

Partially least squares path modeling (PLS-PM) or structural equation modeling (PLS-SEM) is used to estimate complex cause-effect relationships in latent variable models (Hair et al., 2022a). PLS-SEM, in particular, focuses on statistical model estimation through projection and aims to explain causal relationships. This method allows researchers to assess complicated

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models containing many constructs, indicator variables, and structural routes without making explicit assumptions about data distribution (Sarstedt, 2017). Although Partial Least Squares Structural Equation Modeling (PLS-SEM) can be used for smaller sample sizes, it is preferable to employ bigger samples wherever feasible. This technique ensures that the findings may be extrapolated to a larger population (Hair et al., 2022b; Kock & Hadaya, 2018).

The use of PLS-SEM is justified due to its suitability for handling complex models, small sample sizes, and its ability to maximize explained variance, making it ideal for predictive and exploratory research (Hair et al., 2016a; Sarstedt, 2017). Unlike CB-SEM, PLS-SEM is robust to violations of normality and handles formative and reflective constructs effectively. However, its limitations include reliance on bootstrapping, lack of global goodness-of-fit indices, and potential overfitting in intricate models, which require careful interpretation (Sarstedt, 2017; Hair et al., 2022b).

A standardized questionnaire was developed based on reliable evaluations to collect the data and was divided into two sections. The first section had 34 items adapted from Carolus et al. (2023) and was designed to assess participants' understanding of AI ideas, tools, and applications. In addition, a 20-item questionnaire adapted from Avinc and Dogan (2024) was used to assess digital literacy, focusing on participants' abilities to navigate, analyze, and critically participate in digital contexts. Both scales used a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), which ensured consistent and quantitative results. Furthermore, personal information was gathered, such as age, gender, educational background, year of study (for students), years of experience (for academics), and access to AI-related training. The questionnaires were sent out via Google Forms to reach a larger group of participants. Ethical considerations were carefully taken into account to safeguard the rights and privacy of all participants. Prior to beginning the study, an informed consent section was prominently featured at the start of the Google Form. This section provided a detailed explanation of the study's objectives, methods, and scope. Participants were also clearly informed of their right to withdraw at any point without facing any adverse effects and were assured that all of their responses would be kept confidential. Only the researcher had access to the submissions in the Google Form, ensuring that data was managed securely and responsibly. No personally identifiable information beyond what was necessary for analysis was collected, in accordance with ethical guidelines and best practices for participant protection. This method helped gather reliable data from a diverse group of people.

The data for this study was analyzed using the Jamovi Statistical Software. The participant responses were summarized using descriptive statistics such as means and ranges. These statistics served as a platform for future inquiry. The study investigated the link between AI literacy and digital literacy, calculating Pearson correlation coefficients to determine the degree and direction of these correlations. To ensure the results weren't due to chance, basic linear regression was applied to explore how one variable might predict the other. A significance level of $p<0.05$ was used. The goal of this research was to identify meaningful relationships and understand how students' digital literacy and AI literacy are connected.

The validity and reliability of the measurement model were assessed using Cronbach's alpha, with a target threshold of 0.70 or higher, which is generally regarded as sufficient for ensuring internal consistency (Hair et al., 2016; Taber, 2018). This evaluation confirmed the effectiveness and robustness of the survey instruments in measuring the intended constructs. By employing precise statistical methods, the study ensured a thorough and reliable analysis of the data.

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Results and Discussions

Evaluation of Measurement Model

Hamid et al. (2017) emphasized that Cronbach's Alpha and composite reliability are the most used measures for evaluating internal consistency since they assess reliability based on the relationships among observed variables. By this recommendation, the current study employed Cronbach's Alpha to measure internal consistency reliability and obtained values ranging from 0.715 to 0.966. The reported values align with previously established reliability thresholds (Hair et al., 2010). Constructs like "AI Learning" (0.913) and "Digital Literacy" (0.966) have demonstrated high consistency, which is in line with prior research on technology-related constructs (Taber, 2018; Obenza et al., 2023). The quality of the instruments used in this study is summarized in Table 1.

The Composite Reliability (CR) values exceeded the recommended threshold of 0.7, as suggested by Jöreskog (1971), thereby further confirming the consistency of the constructs. For example, "AI Problem Solving" achieved a Construct Reliability (CR) value of 0.910, while "Ethics" reached 0.931. The findings are consistent with those of Obenza et al. (2023) on dependability constructs in education. The Average Variance Extracted (AVE) values were also examined to ensure convergent validity, and all were found to exceed the minimum acceptable threshold of 0.50, as specified by Fornell and Larcker (1981). The construct "AI Learning" demonstrated strong convergent validity with a value of 0.851, similar to findings in other studies on AI-related constructs (Ng et al., 2021; Obenza et al., 2023).

These results collectively validate the measurement model in terms of validity and reliability, thereby providing a sound basis for subsequent regression analysis. This approach is consistent with Obenza et al.'s, (2023) call for rigorous measurement testing in studies investigating the intersection of AI literacy and cognitive factors.

Table 1. Construct Reliability and Validity

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
AI Learning	0.913	0.928	0.945	0.851
AI Literacy	0.729	0.729	0.847	0.648
AI Persuasion Literacy	0.853	0.853	0.911	0.773
AI Problem Solving	0.852	0.869	0.910	0.771
AI emotion Regulation	0.905	0.905	0.940	0.840
Al Self Competency	0.864	0.866	0.898	0.596
Al Self-Efficacy	0.715	0.718	0.875	0.778
Apply	0.927	0.932	0.942	0.731
Detect	0.859	0.878	0.914	0.779
Digital Literacy	0.966	0.967	0.969	0.622
Ethics	0.889	0.890	0.931	0.818
Understand	0.907	0.912	0.928	0.684

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The empirical difference between variables when examining HTMT outcomes is crucial (Henseler et al., 2015). Table 2 compares the HTMT values of the constructions. For example, the HTMT ratio between "AI Literacy" and "AI Self-Competency" is 0.830, "Digital Literacy" and "AI Self-Competency" is 0.851, and "AI Learning" and "AI Literacy" are 0.767. In addition, measures for "AI Problem Solving" and "AI Literacy" are below the critical threshold of 0.85 at values of 0.835, "AI Persuasion Literacy" and "AI Problem Solving" at 0.561, and "Ethics" and "Digital Literacy" at 0.706, which reconfirms good discriminant validity.

The HTMT cut-off is set at 0.90 meaning all constructs should fall below this threshold (Gold et al., 2001). The highest HTMT value, between "Digital Literacy" and "AI Self-Competency", was 0.851. Although showing a very low correlation, the score still suggests strong discriminant validity. The lowest HTMT value is between "AI Persuasion Literacy" and "AI Problem Solving" at 0.561.

For instance, slightly above the threshold values for HTMT, such as 0.830 for "AI Literacy" and "AI Self-Competency", are theoretically explained and thus indicate a possible conceptual relationship. Overall, the results point towards a very good design of the measurement model capable of differentiating between related constructs yet still yielding valid and reliable measures (Henseler et al., 2015; Kline, 2011).

Table 2 : HTMT (Heterotrait-Monotrait Ratio)

HTMT														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
AI Learning (1)														
AI Literacy (2)	0.767													
AI Persuasion Literacy (3)	0.520	0.635												
AI Problem Solving (4)	0.742	0.835	0.561											
AI emotion Regulation (5)	0.620	0.699	0.541	0.631										
Al Self Competency (6)	0.662	0.830	0.580	0.755	0.884									
Al Self-Efficacy (7)	0.748	0.686	0.480	0.693	0.581	0.601								
Apply (8)	0.715	0.887	0.472	0.715	0.596	0.659	0.666							
Detect (9)	0.567	0.620	0.605	0.621	0.547	0.769	0.484	0.649						
Digital Literacy (10)	0.705	0.793	0.719	0.685	0.643	0.851	0.649	0.643	0.703					
Ethics (11)	0.669	0.874	0.713	0.760	0.580	0.857	0.592	0.671	0.808	0.706				
Sex (12)	0.021	0.101	0.124	0.077	0.015	0.131	0.000	0.066	0.075	0.123	0.135			
Understand (13)	0.662	0.690	0.646	0.748	0.595	0.804	0.600	0.709	0.827	0.770	0.887	0.089		
Sex x AI Literacy (14)	0.537	0.814	0.493	0.577	0.503	0.616	0.502	0.627	0.690	0.604	0.614	0.045	0.672	

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Evaluation of Structural Model

Before discussing the structural relationships, it is important to ensure that there is no multicollinearity bias in the regression results. Thus, it is necessary to check the Variance Inflation Factor (VIF). Hair et al. (2019) mentioned that if the VIF values are more than five, then there may be a problem of multicollinearity among the predictor constructs. Further, collinearity problems can also occur at VIF values that are not very high, especially between three and five (Mason & Perreault, 1991; Becker et al., 2014). Ideally, VIF values should remain below or close to three to ensure an unbiased analysis.

As shown in Table 3, all the VIF values are well within range. This guarantees that there is no collinearity issue in the current study. For example, the VIF for predictors like "AI Literacy" on "AI Self-Competency," "AI Self-Efficacy," and "Apply" are all 1.000, indicating that there are no multicollinearity problems. The Variance Inflation Factor (VIF) for "Sex x AI Literacy" and "Digital Literacy" is 2.784, which is less than the maximum of five. Thus, there is no substantial collinearity between these variables.

The highest VIF was observed for "AI Literacy" in relation to "Digital Literacy," with a value of 2.799. While this number is significantly higher, it is still within acceptable limits, indicating that there are no major issues with collinearity (Becker et al., 2014). These findings demonstrate that the predictors are sufficiently independent, ensuring that the structural model's estimations are robust and accurate, lowering the possibility of bias.

Table 3. Variance Inflation Factor

	VIF
AI Literacy -> Al Self Competency	1.000
AI Literacy -> Al Self-Efficacy	1.000
AI Literacy -> Apply	1.000
AI Literacy -> Detect	1.000
AI Literacy -> Digital Literacy	2.799
AI Literacy -> Ethics	1.000
AI Literacy -> Understand	1.000
Al Self Competency -> AI Persuasion Literacy	1.000
Al Self Competency -> AI emotion Regulation	1.000
Al Self-Efficacy -> AI Learning	1.000
Al Self-Efficacy -> AI Problem Solving	1.000
Sex -> Digital Literacy	1.009

As shown in Table 4, the path coefficient of AI literacy on AI self-competency is 0.612, which is highly positive. This reveals that with the increase in students' AI literacy, there will be an increase in their self-competence regarding the application of AI. The statistics are provided below (T = 11.889, P < 0.001), and these reveal how the literacy of AI affects self-competency

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and thereby marks it as the most influential factor. Similarly, the coefficient of the path from AI literacy to AI self-efficacy stands at 0.586, which also represents a very strong positive relation. In other words, with higher AI literacy, students are very confident about the use of AI technologies, and this is found to be true with T = 12.632 and P < 0.001. Moreover, the interaction between AI literacy and digital literacy is moderate yet significant with a coefficient of 0.523 (T = 6.173, P < 0.001). It means that AI literacy contributes to overall digital competencies. However, the interaction effect of sex by x AI literacy on digital literacy is relatively weaker at P = 0.063, so while it does show gender exerts a bit of moderation too, this is still marginal by nature.

These findings are consistent with educational technology research, which shows that AI literacy fosters deeper understanding and practical application of digital tools, a foundational aspect of navigating a technology-driven world (Ng et al., 2021). Carolus et al. (2023) highlight that AI literacy increases students' confidence and competency in using advanced technological tools, enhancing their ability to solve real-world problems. According to Balakrishnan and Dwivedi (2021), cognitive absorption plays a crucial role in the advancement of AI literacy by influencing self-efficacy and skill-building in digital settings. Siddiq et al. (2017) further stress the significance of nurturing digital and AI literacies to empower individuals with critical 21st-century competencies like problem-solving and critical thinking, which are essential for proficient interaction with AI-based technologies.

The correlation between AI literacy and digital literacy is reinforced by the Integrated Literacy Theory (ILT), showing that a blend of different literacy skills aids students in effectively maneuvering through intricate technological landscapes (Passey et al., 2018). In their research, Kong et al. (2021) found that students who possess strong AI literacy demonstrate improved analytical and cognitive skills, which are essential for developing advanced digital competencies. Additionally, Luckin et al. (2016) suggest that integrating AI literacy with digital literacy enhances ethical awareness and decision-making, enabling students to responsibly interact with AI technologies.

Table 4. Path Coefficient

Path Coefficients						
	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	f^2	**T statistics (|O/STDEV|)**	**P values**
AI Literacy -> Al Self Competency	0.612	0.610	0.051	0.599	11.889	0.000
Sex x AI Literacy -> Digital Literacy	0.218	0.217	0.117	0.020	1.862	0.063

The positive relationship between AI literacy and self-efficacy reflects findings from Wang and Lu (2023), who demonstrated that targeted interventions in AI education significantly enhance students' confidence in applying AI tools effectively. Similarly, Joseph et al. (2024) emphasize that peer collaboration and guided AI learning experiences improve students' self-competency, fostering a proactive attitude toward technology adoption. The findings also highlight that gender's moderation effect, while marginal, could reflect broader socio-cultural

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factors affecting technology engagement, as suggested by Canan Güngören et al. (2022). Addressing these nuances may require more targeted educational strategies to reduce disparities and ensure inclusivity in AI literacy programs.

These outcomes align with the assertions of Hair et al. (2019), which indicate that literacy in AI is useful in providing skills to learners as they try to come to terms with a world that is increasingly driven by technology. This is also aligned with Ringle et al. (2012), who found that self-competency and efficacy were central to embracing the latest technological innovations. According to Shmueli et al. (2016), the two literacies are interrelated since they will jointly equip students to face future technological advancements. However, moderation of gender seems to be mild at the edge (P = 0.063). Further research opportunities lie in the study of this result within a population-specific community, Region XI. Longitudinal and diverse populations must be used in the validation of these results and further research into AI literacy, competency, and digital competencies.

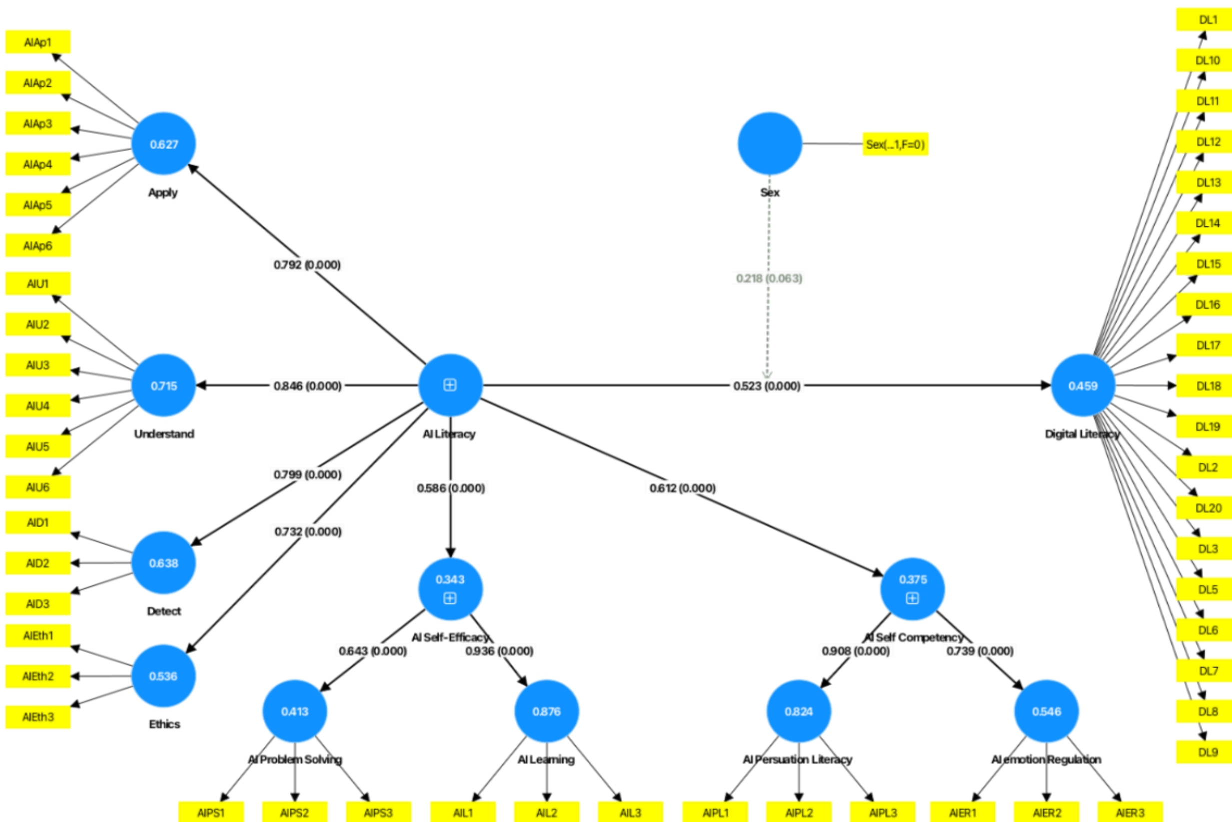

Figure 1: Path coefficients. Results using SmartPLS 4.0

As shown in Table 5, the R-square value for "Digital Literacy" (0.459) indicates that 45.9% of the variance in Digital Literacy is explained by predictors such as AI Literacy, gender, and the interaction effect (Sex × AI Literacy). This demonstrates that AI Literacy is a critical factor in shaping students' digital competencies, though other unmeasured variables also contribute. According to Hair et al. (2016), R-square values between 0.26 and 0.50 suggest moderate explanatory power, underscoring the reliability of the model while highlighting

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opportunities to expand the scope of predictors. These results are consistent with Claro et al. (2012), who highlighted the multifaceted nature of digital literacy, influenced by cognitive abilities, social support, and access to technology.

The strong predictive relevance of the model, as evidenced by a Q² value of 0.431, reflects its robustness in forecasting Digital Literacy outcomes. Shmueli et al. (2016) emphasize the importance of Q² in PLS-SEM for evaluating out-of-sample prediction accuracy, confirming the model's practical relevance in educational research. Additionally, the RMSE value of 0.769 further supports the model's reliability, indicating that prediction errors are minimized. These findings reinforce the argument made by Siddiq et al. (2016) that integrating AI Literacy into educational curricula can effectively enhance students' readiness for digital transformation.

Together, these findings underscore the critical role of AI Literacy in shaping Digital Literacy, highlighting its importance in educational contexts. However, they also call for further exploration of additional determinants to better capture the complex interplay of factors that drive students' digital competencies. This research provides a strong foundation for future studies and supports targeted educational strategies aimed at equipping students with the necessary skills to thrive in an increasingly digital and AI-driven world.

Table 5. Model Fit, Explanatory Power, and Predictive Relevance

	R-square	**R-square adjusted**	**Q² predict**	**RMSE**	**MAE**
Digital Literacy	0.459	0.451	0.431	0.769	0.609
	Saturated model		Estimated model		
SRMR	0.062		0.139		
d_ULS	6.272		31.879		

The model's goodness-of-fit was assessed using key indicators, particularly the Standardized Root Mean Square Residual (SRMR) and d_ULS, as shown in Table 5. The SRMR for the saturated model was 0.062, whereas the estimated model was 0.139. Both numbers are within the allowed range. The results suggest a good alignment between the proposed model and the collected data, with SRMR values below 0.10 indicating a satisfactory model fit (Hair et al., 2019). These findings point to a satisfactory match between the postulated model and the observed data, with SRMR values < 0.10 indicating an acceptable model fit (Hair et al., 2019).

Furthermore, the squared Euclidean distance (d_ULS) was found to be 6.272 for the saturated model and 31.879 for the estimated model. While d_ULS identifies the greatest difference between the observed and estimated covariance matrices, these results indicate that the model is generally consistent, although specific areas of greater disparity may need additional investigation (Henseler et al., 2015).

Together, these indices confirm the reliability and strength of the structural model, demonstrating its effectiveness in elucidating the connections among AI proficiency,

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self-assurance, skills, and digital literacy. This examination affirms that the methodology is sufficiently robust to derive significant insights from the information gathered.

Table 6. Status of Region XI students' AI and digital literacy

Descriptives				
	N	**Mean**	**Mode**	**SD**
Apply AI	206.000	3.500	3.000	0.889
Understand AI	206.000	3.690	3.000	0.852
Detect AI	206.000	3.550	3.000	0.894
AI Ethics	206.000	3.610	3.00	0.875
AI Literacy	206.000	3.590	3.000	0.764
Problem-Solving	206.000	3.340	3.000	0.923
Learn	206.000	3.300	3.000	0.927
AI Self-Efficacy	206.000	3.320	3.000	0.841
Persuasion Literacy	206.000	3.830	5.000	0.966
Emotion Regulation	206.000	3.270	3.000	1.033
AI Self-Competency	206.000	3.550	3.000	0.859

Analyzed data from 206 respondents revealed meaningful insights into the levels of AI-related constructs among college students, as outlined in Table 6. The mean score for "Apply AI" was 3.50, suggesting a high level of practical application skills among students. Similarly, the average scores for "Understand AI" (3.69) and "Detect AI" (3.55) indicate a strong understanding and ability to identify AI applications, respectively. These findings align with prior research emphasizing the growing integration of AI into academic settings, which enhances students' practical and theoretical knowledge of AI (Kong et al., 2022).

For "AI Ethics," the mean score of 3.61 reflects a high degree of ethical awareness, resonating with Wang et al. (2022), who highlighted the importance of integrating ethical principles into AI education. The overall mean for "AI Literacy" was 3.59, signifying that students exhibit high levels of literacy in understanding and interacting with AI technologies. These outcomes reinforce previous studies, such as those by Siddiq et al. (2016), which stress the significance of fostering AI literacy to navigate the ethical and technical complexities of modern technology.

Interestingly, the mean values for "Problem Solving" (3.34), "Learn AI" (3.30), and "Emotion Regulation" (3.27) were slightly lower, indicating moderate levels in these areas. This suggests a potential gap in integrating emotional intelligence and adaptive learning strategies within AI education. Balakrishnan and Dwivedi (2021) similarly noted that cognitive and emotional engagement play a crucial role in enhancing the overall effectiveness of AI-driven learning tools.

The mean for "AI Self-Efficacy" was 3.32, reflecting moderate confidence among students in their ability to utilize AI technologies effectively. These findings correspond to research by Yang et al. (2022), which highlights the need for targeted interventions to boost confidence and proficiency in using AI systems. Lastly, "Persuasion Literacy" achieved the highest mean score of 3.83, emphasizing students' adeptness in discerning and addressing

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persuasive AI tools, as corroborated by Kong et al. (2021), who found similar trends in AI literacy across university students in Hong Kong.

These insights collectively underline the high proficiency of students in applying, understanding, and evaluating AI technologies while revealing areas for further development, particularly in problem-solving and emotional regulation. Future efforts should focus on addressing these gaps to create a more comprehensive and balanced AI literacy framework for students.

Theoretical Implications

This study adds to the theoretical discussion surrounding the relationship between AI literacy and digital literacy by providing clear evidence of their correlation, as well as highlighting the crucial roles of self-confidence and individual abilities. Based on the Integrated Literacy Theory (ILT) model, the findings emphasize the significance of AI literacy in enhancing digital skills, demonstrating its potential to create positive changes in educational settings. The study stresses the importance of self-confidence and skills in converting AI literacy into useful digital abilities, thereby enhancing our comprehension of literacy models in rapidly evolving technological landscapes (Ng, 2012; Passey et al., 2018).

Moreover, the study highlights the moderating role of contextual factors such as gender, offering a nuanced perspective that invites further investigation into how demographic variables influence literacy development. Even though gender was considered to have a minor impact, its incorporation offers opportunities to improve and expand approaches for creating AI literacy initiatives (Henseler et al., 2015).

The findings further support the ILT framework, illustrating how cognitive and technical literacy elements combine to prepare students for technology-driven environments. This reinforces the notion that AI literacy is not an isolated skill, but rather an essential component of overall digital literacy. It integrates ethical understanding, emotional intelligence, and problem-solving abilities. By addressing these gaps, the study provides a theoretical foundation for developing comprehensive literacy models that incorporate technical, ethical, and cognitive elements (Luckin et al., 2016; Obenza et al., 2024).

Conclusion

This study highlights the significance of AI literacy in enhancing digital literacy among students by addressing knowledge gaps and improving technological skills, thereby equipping them to navigate the digital landscape more effectively. The findings show a strong correlation between AI literacy and digital literacy, emphasizing the crucial roles of self-efficacy and competency, while indicating that gender has a minimal moderating effect. A thorough evaluation of the model demonstrated its methodological validity, showcasing high reliability and convergent validity in essential areas such as AI learning and problem-solving, thereby providing empirical support. The structural model further demonstrated the necessity of direct and indirect effects of AI literacy, supporting the mediation hypothesis and illustrating how integrating AI literacy into digital competencies creates a transformative impact, as evidenced by significant path coefficients and moderate explanatory power. In an AI-driven society, it is crucial for students to develop important skills, and integrating these skills into education is vital. This emphasizes the significance of educational structures that consider cognitive and demographic influences on technological abilities.

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Recommendations

The study underscores the need to deliberately focus on educational programs that increase student acceptance of artificial intelligence. Educators should incorporate AI into their curricula across all educational levels, covering not only technical aspects but also ethical, social, and practical considerations. This well-rounded approach will assist students in developing a positive perspective on AI. Policymakers also have a critical role to play in supporting AI-focused initiatives by advocating for educational frameworks that emphasize AI knowledge, allocating resources toward AI research, and financing studies that explore the various factors influencing AI acceptance. It is crucial to examine how expectations regarding performance and effort impact the acceptance of AI. Furthermore, it's important to consider how social factors influence students' perceptions of AI. A comprehensive strategy is needed to build trust, increase awareness, and promote engagement with AI technologies. This approach will enable students to use AI effectively while also understanding its broader societal impacts. Educators and policymakers must collaborate to create a responsible and widely supported future for AI in education.

Limitations and Future Research

This study provides important insights into the connection between AI literacy and digital literacy but also acknowledges several limitations. The cross-sectional design limits the ability to establish causal relationships, underscoring the need for longitudinal studies that monitor changes over time. Furthermore, since the research only focuses on students from Region XI, its relevance to larger populations may be limited. Thus, future studies should include participants from diverse regions, cultures, and socioeconomic backgrounds to enhance the generalizability of the findings. The study also overlooks important mediating factors such as motivation, prior experience with AI tools, and technology acceptance, which could provide deeper insights into literacy development. Additionally, the rapid advancement of AI technology, such as generative AI and machine learning, indicates that the findings may soon become outdated. Therefore, continuous research is necessary to maintain relevance. Additionally, issues such as data privacy, algorithmic bias, trust in AI, and psychological concerns related to AI adoption need further exploration in order to address barriers to AI acceptance. Future studies should examine a broader range of topics and ethical considerations to improve generalizability and relevance.

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