Digital Literacy, Attitudes toward Artificial Intelligence, and AI Literacy among University Students: A Path Analysis Study

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ABSTRACT: *The rapid integration of artificial intelligence (AI) into higher education has heightened the need to understand how students develop AI literacy. This study examined the relationships among digital literacy (DL), attitude toward artificial intelligence (AIA), and AI literacy (AIL), with particular attention to the mediating role of attitudes. A quantitative, cross-sectional design was employed. Data were collected from 214 undergraduate students enrolled in an information systems program at a public university via a structured questionnaire that measured digital literacy, attitudes toward AI, and self-reported AI literacy. Regression-based path analysis with bootstrapping was used to estimate direct and indirect relationships among the study variables.*

The results indicated that DL was positively associated with both AIA and AIL, while AIA was also positively associated with AIL and partially mediated the relationship between DL and AIL. These findings suggest that digital literacy is related to AI literacy both directly and indirectly through attitudes, highlighting the role of cognitive and affective factors in the development of AI literacy. However, given the cross-sectional and self-report nature of the data, these relationships should be interpreted as associations rather than causal relationships. This study provides contextualized empirical evidence from a Southeast Asian higher education setting and contributes to the literature by examining the DL–AIA–AIL framework in an underrepresented context. From a practical perspective, the findings suggest that higher education institutions may benefit from integrating digital skill development with learning experiences that foster positive engagement with AI technologies.

Keywords: Digital literacy; Attitude toward artificial intelligence; AI literacy; Higher education; Path analysis

1. Introduction

Artificial intelligence (AI) has rapidly become a transformative force in education, business, and daily life, reshaping how people learn, make decisions, and prepare for the future by acquiring new skills. Although prior research has established links among digital literacy (DL), attitude toward AI (AIA), and AI literacy (AIL), how these constructs interact may vary across educational contexts, particularly in regions experiencing rapid AI integration. This raises an important question: Does digital literacy translate into AI literacy in the same way across higher education contexts, or is this relationship shaped by students' attitudes toward AI? In such contexts, a positive attitude toward AI may play a vital role in facilitating students' engagement with AI-related learning and in developing AI literacy. Therefore, rather than merely replicating an existing model in a different geographical setting, this study examines whether the relationships among digital literacy, attitude toward AI, and AI literacy manifest differently within a Southeast Asian higher education context. However, existing studies rarely examine how these constructs interact to influence key

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educational outcomes, such as AI learning readiness, academic engagement, and technology-supported learning performance. This gap is particularly relevant for higher education systems undergoing rapid AI integration.

Higher education institutions are increasingly integrating AI tools into teaching, assessment, and administration, raising essential questions about how students develop the competencies needed to navigate these changes. Digital literacy (DL) is widely recognized as a foundational competence for engaging effectively with technology, providing the skills necessary to access, evaluate, and utilize digital resources (Ng, 2012; UNESCO, 2018). Beyond its technical functions, DL also shapes how individuals perceive and respond to new technologies, making it a potential driver of both attitudes toward AI (AIA) and AI literacy (AIL). Recent studies highlight the interconnections among digital literacy, attitudes toward AI, and AI literacy, emphasizing the need to examine these relationships within a unified analytical framework using multivariate techniques such as path analysis.

Digital literacy is widely recognized as a foundational competence in technology-enhanced learning environments (Ng, 2012; UNESCO, 2018). Rather than reiterating its definition, this study focuses on how digital literacy functions within a broader system of relationships involving attitudes toward AI and AI literacy. In higher education, DL is recognized as a fundamental competence that helps learners adapt to new technologies. Sergeeva et al. (2025) found that digital media literacy—encompassing content access, technical understanding, critical evaluation, and creative production—positively influences students' acceptance of generative AI. Similarly, Laru (2025) found that pre-service teachers with stronger digital literacy demonstrated greater AI literacy proficiency, confirming the foundational role of DL in AI-related abilities. Additionally, Yang et al. (2024) reported a positive association between DL and students' awareness of AI ethics, highlighting the importance of DL in promoting the responsible use of AI technologies. These findings collectively highlight that DL not only supports technical proficiency but also shapes positive, informed attitudes toward AI.

AI literacy (AIL) encompasses the ability to understand, apply, and evaluate AI concepts and technologies, making it crucial for students navigating AI-enabled learning environments. AIL includes technological understanding, application abilities, and ethical awareness (Tadimalla & Maher, 2025; Zawacki-Richter et al., 2019). Recent studies show that AIL enhances academic performance and self-efficacy (Bećirović et al., 2025), suggesting its importance in educational and career contexts. Laupichler et al. (2023) developed and validated an AIL scale for non-experts to address the need for reliable measurement tools. Additionally, Li et al. (2025) reported that positive attitudes toward AI increase openness to AI learning, reinforcing a sequence in which foundational digital skills shape positive attitudes that, in turn, foster AIL. However, empirical evidence integrating DL, AIA, and AIL within a single analytical model—particularly in Southeast Asian higher education contexts—remains limited, indicating the need for mediation-focused analyses such as path analysis.

Building on earlier research, three main pathways have been consistently reported: DL affects AIA, DL predicts AIL, and AIA predicts AIL. Recent studies emphasize the mediating role of AIA between DL and AIL, indicating that attitudes act as a psychological bridge in the learning process (Li et al., 2025). These elements form a sequential, mutually supportive process. For instance, Yang et al. (2024) demonstrated that higher DL levels were positively associated with AI ethics awareness, while Sergeeva et al. (2025) observed that DL promotes acceptance of generative AI. AIA, therefore, is not merely a byproduct but a critical driver of learning behaviors associated with AI education. This progression underscores the significance of AIA in motivating deeper engagement with AI tools and AI-related knowledge (Laru, 2025; Li et al., 2025).

Despite these advances, gaps remain in the literature. Much of the existing research has been conducted in Western contexts or specialized professional fields, such as nursing and teacher education, leaving limited evidence from broader university populations in Southeast Asia. Furthermore, although associations among DL, AIA, and AIL have been documented, relatively few studies have examined these relationships simultaneously using mediation or path analysis. As a result, the mechanisms underlying how DL translates into AIL remain insufficiently understood. Earlier investigations have predominantly relied on correlational or multiple regression approaches, which, although helpful in identifying predictors, provide limited insight into the underlying mechanisms linking digital literacy, attitudes, and AI literacy. By adopting path analysis, the present study addresses this limitation by simultaneously estimating direct and indirect effects, thereby offering a more comprehensive understanding of how digital literacy and attitudes toward AI interact to influence AI literacy.

To address these gaps, the present study develops and empirically tests a conceptual model that positions Attitude toward Artificial Intelligence (AIA) as a mediator between Digital Literacy (DL) and AI Literacy (AIL). By employing path analysis with a sample of undergraduate students in Southeast Asia, the study contributes to the literature in three distinct and theoretically grounded dimensions. Conceptually, it extends and refines the DL–AIA–AIL framework by explicitly theorizing attitude toward AI as a core mediating psychological mechanism linking foundational digital competencies to higher-order AI literacy outcomes, thereby providing an integrative link between perspectives from Social Cognitive Theory and UTAUT. Methodologically, advances prior research by applying a mediation-based path-analytic approach that enables the simultaneous estimation of direct and indirect effects, thereby uncovering underlying causal pathways not observable through conventional bivariate or multiple regression techniques.

Contextually, it provides context-sensitive empirical evidence by examining these relationships within Southeast Asian higher education, a context that remains underrepresented in the literature and is likely to exhibit distinct interaction patterns between cognitive and affective factors due to cultural, educational, and technological influences. Collectively, these contributions enhance the theoretical specification of AI literacy development, strengthen methodological rigor in examining mediation mechanisms, and broaden the empirical generalizability of the DL–AIA–AIL framework across diverse educational contexts.

The proposed model is grounded in Social Cognitive Theory (SCT) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which are integrated to provide a complementary explanation of how cognitive competencies, affective mechanisms, and learning outcomes interact in AI-enabled environments.

From an SCT perspective (Bandura, 1986), digital literacy can be conceptualized as a cognitive capability that shapes individuals' self-efficacy and outcome expectations, which, in turn, influence their attitudes toward AI, an affective mediator of learning behavior.

In parallel, UTAUT (Venkatesh et al., 2003) explains how technology-related beliefs—such as perceived usefulness and ease of use—inform attitudes and subsequent engagement with technology. In this study, digital literacy is expected to strengthen both competence beliefs (SCT) and performance and effort expectancies (UTAUT), thereby fostering more positive attitudes toward AI.

These attitudes, in turn, function as a key psychological mechanism that facilitates the translation of foundational digital skills into more advanced AI literacy outcomes.

By integrating SCT and UTAUT, the model captures both internal cognitive–affective processes (SCT) and technology acceptance mechanisms (UTAUT), providing a more comprehensive theoretical foundation for explaining the direct and indirect relationships among digital literacy, attitude toward AI, and AI literacy.

2. Literature Reviews

Artificial intelligence (AI) is changing education and the workplace. It transforms how we learn, how we make decisions, and the skills we need for future jobs. As colleges and universities use AI technologies in teaching and testing, digital literacy (DL) is becoming more critical. Digital literacy is essential for effective engagement with digital platforms and positively influences attitudes toward AI (AIA) and the development of AI literacy (AIL). Recent studies highlight the relationship between these concepts and emphasize the need to test their connections using statistical models, such as path analysis. However, much of the existing research has examined these constructs in isolation or within specific professional or disciplinary contexts, suggesting the need for an integrated analytical framework that captures their combined effects.

2.1 Digital Literacy (DL)

Digital literacy is defined as the ability to access, evaluate, create, and communicate information using digital technologies (Ng, 2012; UNESCO, 2018). In higher education, DL is recognized as a fundamental competence that helps learners adapt to new technologies. Sergeeva et al. (2025) found that digital media literacy, encompassing content access, technical understanding, critical evaluation, and creative production, positively influences students' acceptance of generative AI in higher education. Similarly, Laru (2025) found that pre-service teachers with stronger digital literacy demonstrated greater AI literacy proficiency, confirming the foundational role of DL in AI-related abilities. Additionally, Yang et al. (2024) reported a positive association between DL and students' awareness of AI ethics,

highlighting the importance of DL in promoting the responsible use of AI technologies. Collectively, these findings indicate that DL supports not only technological adaptation but also the development of attitudes and competencies relevant to AI. Notably, prior research suggests that different dimensions of DL—such as critical evaluation and content creation—may exert distinct influences on learning outcomes, highlighting the need for formal modeling of these relationships within an integrated framework.

2.2 Attitude toward Artificial Intelligence (AIA)

Attitudes toward AI reflect how individuals perceive AI technologies and their applications, encompassing both positive and negative views (Schepman & Rodway, 2020). Several factors, including access to accurate information, comfort with digital tools, and prior experiences with AI, influence AIA. Prior research on computer self-efficacy suggests that individuals' confidence in their ability to use technology strongly shapes their attitudes toward technology adoption (Compeau & Higgins, 1995). Research consistently shows that DL improves AIA by building confidence in using technology-rich environments. Sergeeva et al. (2025) found that students' digital media literacy levels were significant predictors of their acceptance of generative AI, particularly in content access and creation. Likewise, Abou Hashish and Alnajjar (2024) demonstrated that nursing students with greater knowledge of digital transformation and digital skills held more favorable attitudes toward AI. These findings highlight a strong link where digital competence fosters positive views of AI. Importantly, emerging research indicates that AIA may function not only as an outcome of digital competence but also as a mediating mechanism linking DL and AI literacy (Li et al., 2025). Although validated instruments for measuring AIA are available (e.g., Schepman & Rodway, 2020; Aktay et al., 2024), relatively few studies have explicitly modeled AIA as a mediator between DL and AIL within a single, integrated analytical framework.

2.3 AI Literacy (AIL)

AI literacy encompasses understanding of AI concepts, applications, and ethical implications, as well as the ability to critically assess and apply AI in real-world contexts (Tadimalla, 2025; Zawacki-Richter et al., 2019). Recent research by Bećirović et al. (2025) has demonstrated that students' AI literacy, encompassing technological skills, application abilities, and critical evaluation, is positively correlated with their academic performance and self-efficacy in higher education. Tadimalla and Maher (2025) emphasized that AIL should be a core component of AI education, extending beyond technical knowledge to incorporate conceptual and ethical dimensions. Furthermore, Laupichler et al. (2023) developed and validated a scale to assess AI literacy among non-experts, addressing a key gap in the reliable measurement of this complex competence in a general population context. This body of research confirms that AIL is not merely an outcome of learning but also a critical factor for effectively engaging with AI educational tools. Positive attitudes toward AI appear to boost AIL, as learners who view AI favorably are more open to acquiring knowledge and skills in this area (Li et al., 2025). Accordingly, prior studies suggest a sequential process in which foundational digital skills foster positive attitudes, which in turn facilitate the development of AI literacy. However, empirical evidence integrating DL, AIA, and AIL in a single model, particularly outside of Western or specialized populations, remains limited. This highlights the need for mediation-oriented analyses, such as path analysis.

2.4 Relationships among Digital Literacy, AI Attitude, and AI Literacy

Building on earlier research, three main pathways have been consistently reported: DL affects AIA, DL predicts AIL, and AIA predicts AIL. Recent studies further emphasize the mediating role of AIA between DL and AIL, suggesting that attitudes can act as a psychological bridge in the learning process (Li et al., 2025). The synthesis of recent research reveals a clear pattern among digital literacy, attitudes toward AI, and AI literacy. These elements are not isolated; they are interconnected in a sequential and mutually supportive process. This framework highlights AIA as a key factor linking basic digital skills to advanced AI competencies. For instance, Yang et al. (2024) demonstrated that higher DL levels were positively associated with AI ethics awareness, suggesting that digital competence is a necessary precursor to understanding AI's complexities. Similarly, Sergeeva et al. (2025) observed that digital media literacy promotes the acceptance of generative AI, reinforcing the idea that digital skills foster openness to new technologies. This progression underscores the significant role of AIA.

Rather than serving solely as outcomes, positive attitudes toward AI appear to motivate deeper engagement with AI learning and skill acquisition. Laru (2025) noted that positive attitudes toward AI enhanced its practical use, while Li et al. (2025) found that a supportive AIA, along with AIL, mediated the connection between career confidence and job-seeking anxiety. Together, these findings indicate that AIA serves as a motivating force, encouraging deeper engagement with AI education.

The process ultimately leads to AI literacy (AIL), which includes technical understanding, ethical awareness, and critical thinking. Evidence shows that individuals with both strong DL and positive attitudes toward AI are more likely to gain advanced knowledge about AI's abilities and limitations (Bećirović et al., 2025; Laru, 2025). This enhanced AIL has real benefits, including better academic performance and increased self-efficacy (Bećirović et al., 2025; Li et al., 2025). In sum, existing evidence supports the view that cultivating positive attitudes toward AI is a key mechanism for transforming foundational digital literacy into advanced AI literacy.

This conclusion aligns with Bandura's (1986) social cognitive theory, which highlights attitudes and perceptions as mediating mechanisms in learning behavior. A synthesis of the reviewed literature and its relevance to the present study's hypotheses is presented in Table 1.

Table 1. Summary of Key Literature on Digital Literacy, AI Attitude, and AI Literacy

Author(s), Year	Context / Sample	Focus	Key Findings	Relevance to Hypotheses
Sergeeva et al. (2025)	Higher education students (Russia)	Digital media literacy and generative AI	DL positively predicted students' acceptance of generative AI, particularly through content access and creation skills.	Supported H1 (DL → AIA).
Laru (2025).	Pre-service teachers (Europe)	Antecedents of AI literacy	DL positively and significantly predicted AIL competencies.	Supported H2 (DL → AIL).
Yang et al. (2024)	Nursing students (Taiwan)	DL and AI ethics awareness	Higher DL was positively associated with greater awareness of AI ethics.	Supported the link between DL and AIL (ethical dimension).
Abou Hashish & Alnajjar (2024)	Nursing students (UAE)	Digital transformation knowledge and AI	Higher digital proficiency was associated with more favorable AIA.	Supported H1 (DL → AIA).
Li et al. (2025)	Chinese undergraduates	AI attitudes and literacy as mediators	Positive AIA mediated the relationship between career self-efficacy and AIL, reducing job-seeking anxiety.	Supported H3 (AIA → AIL) and H4 (Mediating effect).
Bećirović et al. (2025)	University students (Bosnia)	AI literacy and academic performance	AIL significantly predicted academic performance and self-efficacy.	Reinforced the role of AIL as an outcome variable.
Tadimalla & Maher (2025)	Conceptual paper	AI literacy in education	AIL was conceptualized as a core component of AI education, including knowledge, skills, and ethics.	Provided a theoretical foundation for AIL.
Schepman & Rodway (2020)	General population (UK)	Attitudes toward AI scale validation	Positive AIA significantly predicted the use of AI in daily life.	Supported H3 (AIA → AIL).
Zawacki-Richter et al. (2019)	Systematic review	AI in higher education	Identified AIL as a crucial factor for AI adoption and application in education.	Reinforced the framework linking DL, AIA, and AIL.

2.5 Gap Identification and Hypothesis Development

Although these studies provided valuable insights, several gaps remain. First, most prior research has been conducted in Western contexts or within specialized professional groups such as nursing students and pre-service teachers, leaving limited empirical evidence from broader university populations in Southeast Asia. Second, while associations among DL, AIA, and AIL have been documented, relatively few studies have employed path analysis or mediation models to examine both direct and indirect effects simultaneously.

To address these gaps, the present study develops and tests a conceptual model that positions AIA as a mediator between DL and AIL. Drawing on the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and supported by recent empirical findings, the following hypotheses are proposed:

H1: Digital Literacy (DL) has a positive and significant influence on Attitude toward Artificial Intelligence (AIA).

H2: Digital Literacy (DL) has a positive and significant influence on AI Literacy (AIL).

H3: Attitude toward Artificial Intelligence (AIA) has a positive and significant influence on AI Literacy (AIL).

H4: Attitude toward Artificial Intelligence (AIA) mediates the relationship between Digital Literacy (DL) and AI Literacy (AIL).

Table 2. Summary of Research Hypotheses

Hypothesis	Path Relationship	Theoretical / Empirical Basis
H1	DL → AIA	Higher DL was associated with greater confidence and openness toward technology, leading to more positive attitudes (Sergeeva et al., 2025; Abou Hashish & Alnajjar, 2024). This is consistent with the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003).
H2	DL → AIL	Individuals with greater DL were better positioned to acquire AI literacy competencies (Laru, 2025).
H3	AIA → AIL	Positive AIA significantly predicted greater engagement with AI and enhanced AI literacy (Schepman & Rodway, 2020; Li et al., 2025).
H4	DL → AIA → AIL	AIA partially mediated the relationship between DL and AIL, functioning as a psychological mechanism (Li et al., 2025).

As summarized in Table 2, these hypotheses capture both direct and indirect pathways linking DL, AIA, and AIL. Together, they form a coherent conceptual framework that positions digital literacy as a foundational competence, attitude toward AI as a mediating psychological mechanism, and AI literacy as the resulting advanced capability. Figure 1 presents the conceptual framework that guides the subsequent path analysis.

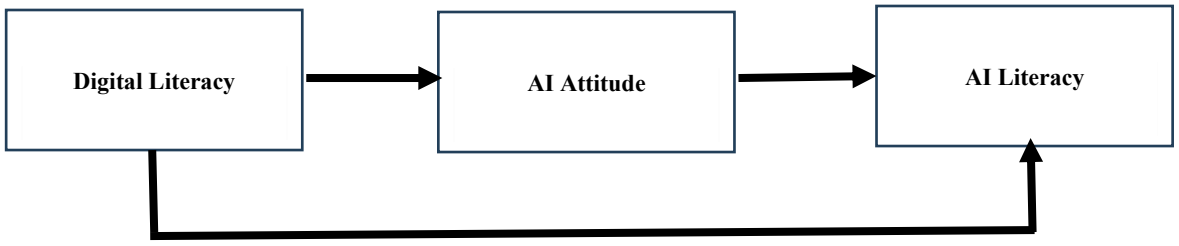


Figure 1. Conceptual Framework

3. Methodology

3.1 Population/Sample

The target population consisted of 388 undergraduate students enrolled in the information systems program within the Faculty of Business Administration. From this population, 214 students voluntarily participated in the study, representing approximately 55% of the total student body. Eligibility criteria required participants to be currently enrolled in an information system–related program and to have prior experience using digital technologies or AI-based tools in their coursework. The focus on undergraduate students is justified because they represent a critical population transitioning into AI-mediated learning environments. Their digital readiness and attitudinal disposition directly influence the success of AI-enabled pedagogical innovations.

To confirm that the sample size was adequate for hypothesis testing, and a priori power analysis was conducted using G*Power version 3.1.9.7 (Faul et al., 2009). Parameters were specified for multiple regression analysis with a significance level (α) of .05, statistical power ($1 - \beta$) of .80, and a medium effect size ($f^2 = 0.15$), following Cohen's recommendations (Cohen, 1988) The results showed that the minimum required sample sizes were 55 participants for a model with one predictor and 68 participants for a model with two predictors. The actual sample of 214 respondents

exceeded both thresholds, resulting in a post hoc power greater than .99. This ensured sufficient sensitivity to detect medium-sized effects and to accurately estimate both direct and indirect relationships in the proposed path model.

3.2 Instrument

Data were collected using a structured questionnaire that was developed and adapted to align with the study's objectives. The instrument comprised four major sections:

*Section 1: Demographic Information***.** Checklist-style items captured demographic information, including gender, age, year of study, and frequency of AI platform use. These data were used to describe the sample and contextualize the findings.

Section 2: Digital Literacy. Measured using 14 items adapted from the Digital Literacy Awareness Scale of Promsri (2019). Items were rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Reliability analysis showed strong internal consistency (Cronbach's $\alpha = .921$).

Section 3: Attitude Toward Artificial Intelligence. Assessed using 20 items adapted from the Artificial Intelligence Attitude Scale developed by Aktay, Gok, and Yildirim (2024). Responses were rated on the same five-point Likert scale.

The reliability coefficient for this section was $\alpha = .912$, indicating excellent internal consistency.

Section 4: AI Literacy. Measured through 35 items assessing knowledge, applications, and ethical implications of AI, based on established AI literacy frameworks (Zawacki-Richter et al., 2019; Laupichler et al., 2023; Tadimalla & Maher, 2025), and adapted to the study context. A five-point Likert scale was used (1 = Strongly Disagree to 5 = Strongly Agree). The scale demonstrated high reliability (Cronbach's $\alpha = .979$). It is important to note that this measure reflects self-assessed (perceived) AI literacy rather than objectively tested competence. Accordingly, the construct captures respondents' subjective evaluation of their understanding and ability to engage with AI technologies, which may differ from actual performance-based proficiency.

To ensure content validity, the questionnaire was reviewed by three subject-matter experts. The Index of Item–Objective Congruence (IOC) values ranged from .67 to 1.00 across all items, exceeding the recommended threshold of .50 (Rovinelli & Hambleton, 1977). Construct validity was examined through exploratory factor analysis (EFA) conducted using principal axis factoring with varimax rotation. Prior to extraction, sampling adequacy was confirmed using the Kaiser–Meyer–Olkin (KMO) measure, and Bartlett's test of sphericity was found to be significant ($p < .001$), indicating suitability for factor analysis. Factors were retained based on eigenvalues greater than 1.00 and inspection of the scree plot. All items demonstrated factor loadings above the recommended threshold of .40 (Hair et al., 2019), with no substantial cross-loadings observed, supporting the unidimensionality of each construct. Given that the measurement scales were adapted from prior studies, additional steps were taken to ensure contextual validity. All items were reviewed and slightly reworded to reflect the AI-enabled higher education context of this study. A pilot test was conducted with a small group of students ($n = 30$) to assess clarity and relevance, and minor revisions were made based on participant feedback. These procedures helped ensure that the adapted instruments maintained both content validity and contextual appropriateness. Internal consistency was further confirmed, as all scales exceeded the recommended reliability threshold of 0.70 (Nunnally & Bernstein, 1994), indicating strong construct reliability. A summary of the results is presented in Table 3.

Table 3. Summary of Validity and Reliability of Research Instruments

Instrument	No. of Items	IOC Range	Factor Loading Range	Cronbach's α
Digital Literacy	14	.67 – 1.00	.439 – .879	.921
AI Attitude	20	.67 – 1.00	.658 – .813	.912
AI Literacy	35	.67 – 1.00	.541 – .824	.979

3.3 Procedures

Data were collected through an online questionnaire distributed via Google Forms. A structured sampling procedure was employed to invite participants from the target population using the official student roster. Eligible students were contacted and invited to participate voluntarily via an online survey link. This approach facilitated efficient data collection while maintaining consistency in participant eligibility.

The inclusion criteria required that participants be undergraduate students majoring in information systems within the Faculty of Business Administration, provide informed consent, and complete the questionnaire in full. Exclusion criteria were applied to individuals who did not provide consent, to responses with substantial missing data that made the questionnaire unusable, and to participants who withdrew before completing the survey.

Participation in the study was entirely voluntary, and informed consent was obtained electronically before data collection. The questionnaire was administered anonymously; no personally identifiable information was collected, and all responses were kept strictly confidential. The study involved no intervention, manipulation, or collection of sensitive personal data, and all procedures adhered to standard ethical principles for educational research.

3.4 Data Analysis

Before hypothesis testing, the dataset was screened for completeness and accuracy. Statistical assumptions, including normality, linearity, homoscedasticity, and multicollinearity, were examined and met the required thresholds, supporting the appropriateness of regression-based path analysis.

Descriptive statistics were computed to summarize respondents' demographic characteristics and the distributions of key study variables. Reliability and validity analyses were conducted for all measurement instruments (see Table 3). Construct validity was assessed through factor analysis, and internal consistency was confirmed using Cronbach's alpha. For the interpretation of mean scores, the following criteria, adapted from Best (1977), were applied:

1.00–1.50 = Very Low
1.51–2.50 = Low
2.51–3.50 = Moderate
3.51–4.50 = High
4.51–5.00 = Very High

Path analysis was subsequently performed using regression-based procedures in SPSS (Version 27). Both direct and indirect effects among digital literacy (DL), attitude toward AI (AIA), and AI literacy (AIL) were estimated, with statistical significance evaluated at the .05 alpha level. Indirect effects were examined using a bootstrapping procedure to test for mediation. Specifically, bias-corrected bootstrap confidence intervals were generated from 5,000 resamples, following recommendations from Preacher and Hayes (2008). Mediation was considered statistically significant when the 95% confidence interval did not include zero. This approach provides a more robust estimate of indirect effects than traditional methods, as it does not assume normality of the sampling distribution.

4. Results

This section presents the results of the data analysis, beginning with the respondents' demographic characteristics and followed by the descriptive statistics for the primary constructs. Subsequent analyses included descriptive statistics, assumption testing, and path analysis to examine the hypothesized relationships among digital literacy, attitudes toward AI, and AI literacy.

4.1 Demographic Characteristics

Table 4. Demographic Characteristics of Participants (n = 214)

Variable	Category	n	Percentage (%)
Gender	Male	131	61.2
	Female	83	38.8
Age	18–20 years	79	36.9
	20 years and up	135	63.1
Year of Study	Year 1	37	17.3
	Year 2	6	2.8
	Year 3	91	42.5
	Year 4	80	37.4

As shown in Table 4, 214 undergraduate students participated in the study. Of these, 131 were male (61.2%), and 83 were female (38.8%). Regarding age, 79 participants (36.9%) were aged 18-20, while the majority, 135 students (63.1%), were aged 20 or older. With respect to year of study, 37 students (17.3%) were in their first year, 6 (2.8%) in their second, 91 (42.5%) in their third, and 80 (37.4%) in their fourth. These demographic characteristics indicate representation across multiple age groups and academic years, with a higher proportion of male students.

4.2 Descriptive Statistics

Table 5. Descriptive Statistics of Key Variables (n = 214)

Variable	*M*	*SD*	Interpretation
Digital Literacy	3.85	0.66	High
AI Attitude	3.68	0.62	High
AI Literacy	3.33	0.78	Moderate

Table 5 presents the descriptive statistics of the study's key variables. Digital Literacy (DL) had the highest mean score (M = 3.85, SD = 0.66), suggesting that respondents rated themselves relatively highly in digital skills. AI Attitude (AIA) yielded a mean of 3.68 (SD = 0.62), indicating overall positive perceptions toward AI. AI Literacy (AIL), with the lowest mean (M = 3.33, SD = 0.78), revealed that participants' self-assessed understanding of AI concepts was moderate compared to their literacy and attitudes. Overall, the descriptive results indicate relatively high levels of digital literacy and positive attitudes toward AI, while AI literacy was rated as moderate.

4.3 AI Platform Usage

Table 6. Top Three AI Platforms Used by Respondents (n = 214)

Rank	Platform	Frequency (n)	Percentage (%)
1	ChatGPT	74	34.6
2	Google Gemini	55	25.7
3	Microsoft Copilot	40	18.7

As shown in Table 6, ChatGPT was the most widely used AI platform, reported by 74 respondents (34.6%). Google Gemini ranked second, with 55 respondents (25.7%) reporting its use, while Microsoft Copilot ranked third with 40 respondents (18.7%). Together, these three platforms accounted for the majority of respondents' reported AI usage.

4.4 Path Analysis and Hypothesis Testing

Before conducting the path analysis, preliminary assumption checks were performed to ensure the validity and reliability of the results. The data were found to approximate a normal distribution (normality) and exhibited linear relationships among the study variables. Multicollinearity was assessed using Tolerance and Variance Inflation Factor (VIF) values, which indicated no concern: all Tolerance values exceeded 0.10, and all VIF values were below 5, consistent with recommended thresholds (Hair et al., 2019). Additionally, the assumption of homoscedasticity was met, as the residuals exhibited consistent variance across the predicted values. These findings confirmed that the dataset satisfied the essential assumptions for regression-based path analysis. All hypothesis tests were subsequently conducted at a significance level of $\alpha = .05$. The results of hypothesis testing were summarized in Table 5.

Table 7. Results of Hypothesis Testing for the Path Model

Hypothesis	Path	β	95%CI	p	Result
H1	DL → AIA	.711	-	< .001	**Supported**
H2	DL → AIL (Direct Effect)	.371	-	< .001	**Supported**
H3	AIA → AIL	.288	-	< .001	**Supported**
H4	DL → AIA → AIL (Indirect Effect via AIA)	.205	[.095, .413]	< .001	**Supported**

As summarized in Table 7, all hypothesized relationships were supported. Digital Literacy (DL) significantly predicted AI Attitude (AIA; $\beta = .711$, $p < .001$), supporting H1. DL was also positively associated with AI literacy (AIL; $\beta = .371$, $p < .001$), supporting H2. In addition, AIA was positively associated with AIL ($\beta = .288$, $p < .001$), supporting H3. The indirect effect of DL on AIL through AIA was statistically significant ($\beta = .205$, 95% CI [.095, .413]), indicating that attitude toward AI partially mediated the relationship between digital literacy and AI literacy, thereby supporting Hypothesis 4.

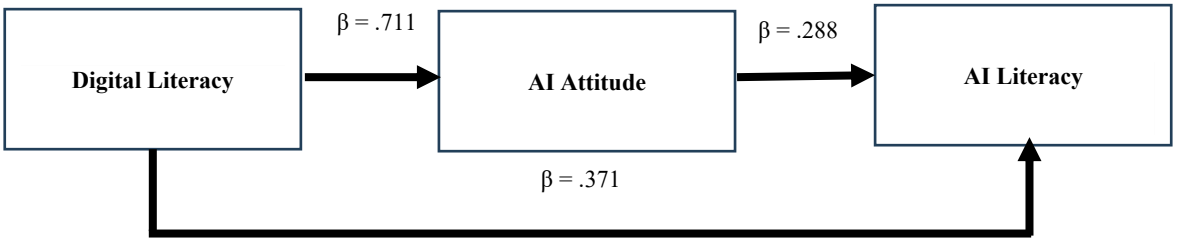


Figure 2. Path analysis

Figure 2 illustrates the path analysis model depicting the relationships among digital literacy (DL), attitude toward AI (AIA), and AI literacy (AIL). Standardized coefficients are reported, and all paths were statistically significant at $p < .001$. Digital literacy was positively associated with attitude toward AI ($\beta = .711$) and AI literacy ($\beta = .371$), while attitude toward AI was also positively associated with AI literacy ($\beta = .288$). The indirect effect of DL on AIL through AIA was positive ($\beta = .205$), indicating partial mediation. The total effect of DL on AIL was also significant ($\beta = .576$, $p < .001$). These findings suggest that both direct and indirect pathways are involved, with attitudes toward AI contributing to the relationship between digital literacy and AI literacy.

5. Discussion

This study examined the mediating role of Attitude toward Artificial Intelligence (AIA) in the relationship between Digital Literacy (DL) and AI Literacy (AIL) among undergraduate students. The empirical evidence confirmed all proposed hypotheses, reinforcing the conceptual model and offering nuanced insights into how foundational digital skills and psychological attitudes jointly shape AI-related competencies.

The results indicate a strong positive association between digital literacy and attitudes toward AI, suggesting that students with higher levels of digital competence tend to report more favorable perceptions of AI. Rather than merely confirming prior findings, this result highlights the role of digital literacy as a foundational condition that may shape students' readiness to engage with emerging technologies in AI-enabled learning environments. In the present study, respondents reported the highest mean score for DL, suggesting that digital proficiency is a well-developed competence among the sample and functions as a precursor to attitudinal readiness for AI adoption, a critical prerequisite for technology integration (Venkatesh et al., 2003).

DL was positively associated with AIL, suggesting that higher levels of digital competence are linked to stronger self-reported AI literacy. This finding is consistent with Laru (2025), who demonstrated that digital literacy significantly predicts AI-related knowledge and competencies among pre-service teachers. The current results extend this evidence by showing that stronger DL equips students not only to acquire AI-related knowledge but also to apply it in practical educational contexts, thereby supporting DL's role in AI education.

The analysis further indicated that AIA was significantly associated with AIL. This finding is consistent with prior studies (Schepman & Rodway, 2020; Li et al., 2025), which suggest that positive attitudes toward AI are related to greater motivation and engagement with AI tools. Although AIL had the lowest mean score among the three constructs, this result highlights the importance of learners' perceptions and confidence in supporting the development of AI-related competencies.

This finding should be interpreted considering the measurement approach. In this study, AI literacy reflects respondents' self-reported (perceived) competence rather than objectively assessed skills. Accordingly, the results indicate differences in perceived readiness and confidence in engaging with AI, rather than definitive differences in actual proficiency. This distinction is important, as prior research suggests that perceived competence can influence motivation, engagement, and learning behavior, even when it does not fully align with objective ability.

Most importantly, the findings indicate that AIA partially mediates the relationship between DL and AIL. This suggests that digital literacy may contribute to AI literacy both directly and indirectly through attitudes. Rather than implying a definitive causal mechanism, these results provide empirical support for a cognitive–affective pathway proposed in

prior research. The mediation effect confirmed through bootstrapping further strengthens the robustness of this interpretation. This finding resonates with Bandura's (1986) social cognitive theory, which emphasizes the role of perceptions and attitudes as mediators in shaping learning behaviors. The present contribution lies in empirically demonstrating this mediating effect among Southeast Asian undergraduates, thereby extending prior models to an underrepresented context in the literature.

From an educational perspective, these findings suggest that improving AI literacy may require attention not only to technical skill development but also to learners' psychological readiness. Fostering positive attitudes toward AI may support students' engagement with AI-related learning, thereby contributing to the development of AI literacy.

Beyond its contextual implications, this study offers theoretical refinement by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) with Social Cognitive Theory (SCT) to explain the development of AI literacy as a multi-dimensional learning outcome. While UTAUT emphasizes the role of technology-related beliefs—such as performance expectancy and effort expectancy—in shaping behavioral intention and technology use, SCT highlights the importance of cognitive capabilities and self-efficacy in driving learning processes and outcomes.

The present findings suggest that digital literacy operates at the intersection of these frameworks: it functions both as a cognitive capability (SCT) and as a foundation for the formation of technology-related beliefs (UTAUT). Importantly, attitude toward AI emerges as a central affective mechanism that links these domains and mediates the relationship between competence and learning outcomes. Empirically, the significant indirect effect observed in this study supports this integrative mechanism, demonstrating that digital literacy influences AI literacy not only directly but also indirectly through attitudinal pathways.

This integration extends prior applications of UTAUT, which have primarily focused on technology adoption, by demonstrating its relevance for explaining higher-order competencies, such as AI literacy, when combined with SCT's emphasis on cognitive–affective processes. Accordingly, the findings reposition attitude toward AI as a critical bridge between foundational skills and advanced learning outcomes in AI-enabled educational contexts.

An essential finding of this study is the mediating role of attitude toward AI in the relationship between DL and AIL. Rather than emphasizing solely direct skill-based pathways, these findings suggest the relevance of social–psychological factors in AI literacy development. The results also indicate that contextual conditions may shape how technology acceptance mechanisms operate across educational settings. Accordingly, instructional strategies that promote positive engagement with AI—such as peer-supported learning and contextualized use cases—may help develop AI literacy. These findings highlight the importance of considering both contextual and affective dimensions when designing AI literacy interventions (Hofstede, 2001; House et al., 2004).

The present study contributes to the literature by empirically examining the DL–AIA–AIL framework within a Southeast Asian higher education context, a population and setting that have been underrepresented in prior research. Whereas earlier studies have predominantly examined these constructs in Western or professional domains (Laru, 2025; Li et al., 2025), this research broadens the scope by focusing on a general university population. The findings suggest that strengthening digital literacy alone may not be sufficient and that positive attitudes toward AI may also play an important role in developing AI literacy. This contribution is theoretically meaningful, as it extends existing models of technology adoption, and practically relevant, as it provides insights for designing curricula that integrate digital and AI competencies in higher education.

Building on these insights, this study offers a conceptual perspective that highlights the potential role of attitudes in shaping the relationship between digital literacy and AI-related learning outcomes. This perspective suggests a dual approach to curriculum design: (1) strengthening digital literacy (DL) and (2) fostering positive attitudes toward AI (AIA). Attitude toward AI may serve as an important affective component in the development of AI literacy. Practical strategies may include incorporating locally relevant AI use cases, integrating discussions on ethical AI to reduce uncertainty, and providing sandbox environments where students can explore AI tools in a low-risk setting.

Institutions that focus primarily on technical skill development without sufficient attention to attitudinal factors may experience more limited outcomes in AI literacy initiatives. The findings suggest that positive attitudes toward AI may serve as an important facilitator, potentially helping translate digital skills into more advanced AI-related competencies.

Empirically, although the present data were derived from a single-institution sample, exploratory analyses indicated generally consistent patterns across gender and AI-use frequency. However, prior research suggests that factors such as academic discipline and prior experience may moderate these relationships (Lam et al., 2014; Fathema et al., 2020). Accordingly, future research could apply multi-group path analysis or structural equation modeling (SEM) to further examine potential structural differences across subpopulations. In addition, incorporating performance-based assessments—such as problem-solving tasks or simulation-based AI exercises (Laupichler et al., 2023)—may help strengthen construct validity and reduce potential bias associated with self-report measures.

From a methodological perspective, this study employs path analysis to examine the interrelationships among DL, AIA, and AIL. The identification of a partial mediation pattern suggests the presence of both direct (skills-related) and indirect (attitude-related) pathways linking digital literacy and AI literacy. Compared with conventional regression approaches, this method may provide a more nuanced understanding of these relationships by accounting for indirect associations. Accordingly, the analytical approach adopted in this study may offer a useful framework for exploring the interplay between cognitive and affective factors in AI literacy development. These findings should be interpreted with caution, given the reliance on self-report, cross-sectional data.

6. Conclusions

This study examined the relationships between digital literacy (DL), attitude toward AI (AIA), and AI literacy (AIL) among university students. The results showed that DL was positively associated with AIL, both directly and indirectly through AIA, with AIA acting as a partial mediator. These findings suggest that technical skills alone are insufficient; psychological readiness, as demonstrated by positive attitudes toward AI, is equally essential for developing AI literacy. Accordingly, the findings highlight the need for a balanced approach that integrates both skill development and attitudinal support in AI-related education.

From a theoretical perspective, this study provides contextualized empirical support for the DL–AIA–AIL framework in a Southeast Asian higher education setting, contributing evidence from a population underrepresented in prior research. The findings also offer implications for the application of the Unified Theory of Acceptance and Use of Technology (UTAUT), suggesting that attitudes toward AI may play an important role in shaping higher-order literacy outcomes.

From a practical perspective, the findings offer guidance for curriculum and policy development related to AI literacy. In line with UNESCO's (2021) recommendations on AI ethics and the AI literacy framework proposed by Long and Magerko (2020), universities may consider adopting an integrated instructional approach that includes: (1) strengthening digital literacy with a focus on access, evaluation, and ethical awareness; (2) fostering positive attitudes toward AI through reflective and collaborative learning experiences; and (3) incorporating applied AI literacy activities that emphasize creativity, ethical reasoning, and responsible use. This integrated approach may support students' engagement with AI in academic contexts and inform similar initiatives in comparable educational settings.

The findings are noteworthy as they suggest that attitudes toward AI may function as a psychological mechanism linking digital literacy and AI literacy. However, given the cross-sectional and self-report nature of the data, these relationships should be interpreted as associations rather than causal relationships.

Empirically, although the study was conducted within a single institution, the results indicated generally consistent patterns across gender and AI-use frequency. Future research could employ multi-group path analysis or structural equation modeling (SEM) to examine potential structural differences across subpopulations. In addition, incorporating performance-based measures—such as AI problem-solving or simulation tasks (Laupichler et al., 2023)—may help strengthen construct validity and reduce reliance on self-reported data.

Overall, the findings contribute to a growing body of research on AI literacy by offering theoretical, methodological, and practical insights into how digital literacy and attitudes toward AI relate to the development of AI literacy in higher education contexts.

7. Implications and future research

7.1 Practical implications

Building on the empirical findings, the following recommendations outline how the results can guide educational practice and curriculum design in higher education:

1. Foster Positive Attitudes toward AI. Given the observed relationship between AIA and AIL, educational initiatives may benefit from extending beyond technical training to include affective learning components. Incorporating experiential activities that provide positive, low-stress interactions with AI—such as project-based assignments using widely adopted tools (e.g., ChatGPT, Google Gemini, and Microsoft Copilot)—may help students recognize AI's practical relevance and become more comfortable using it in academic contexts.
2. Strengthen Digital Literacy as a Foundational Competency. Higher education institutions may benefit from establishing digital literacy programs that are accessible across disciplines. Emphasis may be placed on the critical evaluation of online information, responsible data use, and proficiency with diverse digital tools. These competencies provide a foundation for engaging with more advanced AI-related learning.
3. Implement Integrated, Sequential Curricula. Given the observed relationships among the study variables, higher education institutions may benefit from designing integrated learning experiences that simultaneously support digital skill development and foster positive engagement with AI. Rather than treating these elements as separate domains, coordinated instructional strategies may enhance students' readiness to interact with AI technologies in meaningful ways.
4. Institutionalize Attitude-Focused Learning Approaches. In line with the study's findings, universities may benefit from treating attitudinal development as an explicit learning objective. Learning activities that address ethical considerations, social implications, and locally relevant examples of AI use may help reduce uncertainty, encourage curiosity, and support more positive engagement with AI technologies.
5. Integrate AI Literacy into Curriculum Design. For curriculum developers and instructors, the findings suggest the importance of embedding AI literacy within undergraduate programs through learning activities that support both skill development and positive perceptions of AI. At the institutional level, aligning curriculum guidelines with ethical and pedagogical considerations may help enhance readiness for AI-enabled education.

Overall, these implications suggest that developing AI literacy involves balancing cognitive skill development with affective support. Effective AI education may therefore benefit from attention to both competencies and learner attitudes, rather than focusing solely on technical training.

7.2 Limitations and future research

Although this study provides valuable insights, several limitations should be acknowledged, which in turn suggest directions for future research.

1. Population and Context. This study was conducted within a single institution and academic program, which may limit the transferability of the findings to other higher education contexts. Institutional characteristics, disciplinary focus, and local learning environments may influence the relationships observed among digital literacy, attitudes toward AI, and AI literacy. As such, the findings should be interpreted with caution when applied to different institutional or disciplinary settings. Future research could extend the investigation across multiple institutions, academic disciplines, and national contexts to examine the consistency of these relationships and enhance the generalizability of the results.
2. Research Design. This study relies on self-report data collected at a single point in time, which introduces several methodological limitations. First, self-report instruments may be subject to common method bias and social desirability effects, potentially affecting response accuracy. In addition, the cross-sectional nature of the data limits causal inference, as the observed relationships reflect associations rather than definitive cause-and-effect mechanisms. Future research is encouraged to employ longitudinal designs, multi-source data (e.g., behavioral or system-generated data), or performance-based assessments to enhance the robustness and validity of the findings.
3. Methodological Approach. In addition, all constructs were measured using self-reported instruments, which may introduce common method bias and social desirability effects. Respondents may overestimate their digital competencies or AI-related abilities, potentially inflating the observed relationships among variables. Although procedural remedies, such as anonymity and the use of validated scales, were implemented, shared method variance cannot be entirely ruled out. Accordingly, the findings should be interpreted with caution. Future research could address this limitation by adopting a multi-method approach, including objective performance-based assessments, behavioral data, and instructor evaluations, to provide a more comprehensive assessment of AI-related competencies.

4. Analytical Techniques. Although regression-based path analysis was appropriate for the present study, future research may employ structural equation modeling (SEM) to assess overall model fit, test alternative models, and examine more complex relationships among constructs.
5. Platform-Specific Effects. Given that ChatGPT, Google Gemini, and Microsoft Copilot were the most frequently used AI platforms among participants, future research could examine whether different AI tools vary in their influence on attitudes toward AI and AI literacy development. Such analyses may yield more granular insights for educational technology design.
6. Evaluation of Educational Interventions. Future studies could empirically test instructional interventions derived from the study's findings by comparing learning outcomes between curricula that integrate attitudinal components and those that focus primarily on technical skill development.

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