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Multidimensional AI Literacy and Students' Acceptance of AI-Enabled Learning Technologies: A Higher-Order Extension of the Technology Acceptance Model

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Research Article

Keywords: AI literacy. AI-enabled learning. Technology Acceptance Model (TAM). higher education. PLS-SEM. responsible AI use

Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11407016/v1

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Additional Declarations: No competing interests reported.

Abstract

AI-enabled learning technologies are becoming routine in higher education. However, acceptance research tends to explain adoption through beliefs about technology while paying less attention to the capabilities that learners bring to AI interaction. Although AI literacy has recently been linked to acceptance, it is often modeled as a global score or as separate dimensions, leaving unresolved whether related competencies operate collectively within the Technology Acceptance Model (TAM) mechanism. This study tests a higher-order extension of the TAM using survey data from 528 students across three Indonesian universities who had prior experience with AI for learning. AI literacy was specified through awareness, usage skills, critical understanding, and ethics awareness and estimated using a disjoint two-stage partial least squares structural equation modeling procedure. The results support a coherent higher-order representation and show that AI literacy is most strongly associated with perceived ease of use and is also positively related to perceived usefulness and attitude. Within TAM, attitude shows a stronger direct relationship with behavioral intention than usefulness. These findings position AI literacy as a learner capability layer that complements technology beliefs in explaining students' evaluations of AI-enabled learning technologies. The study contributes a measurement-to-mechanism perspective that maintains practical, critical, and ethical competence in acceptance research and suggests that implementation should consider learner capability alongside access and usability. Because the evidence is cross-sectional, self-reported, and multi-tool, the relationships should be interpreted as associations rather than causal effects.

1 Introduction

Artificial intelligence (AI) has rapidly transitioned from a specialist technology to a routine component of university learning. Students now use generative AI chatbots, writing assistants, translation systems, image generators, and other AI-enabled applications to explain concepts, generate or revise text, analyze information, and support problem solving. Reviews of generative AI in education emphasize both substantial learning affordances and persistent concerns about accuracy, overreliance, academic integrity, and the quality of human judgment (Jo, 2024; Wang et al., 2024; Walter, 2024). Meta-analytic evidence also suggests that generative AI can improve learning outcomes under certain instructional conditions, although the effects vary by design and context (Liu et al., 2025; Sun & Zhou, 2024). Therefore, for educational technology research, the important question is not simply whether students encounter AI, but how learner capabilities and technology evaluations are jointly related to informed use.

Technology acceptance research offers a well-established account of how users evaluate digital technologies. In the Technology Acceptance Model (TAM), perceived ease of use and perceived usefulness shape attitude and behavioral intention (Davis, 1989), and recent studies continue to find these beliefs relevant to students' acceptance of ChatGPT and other AI applications (Hazaimeh & Al-Ansi, 2024; Karan & Chakma, 2026; Kim & Moon, 2025; Zhao et al., 2026). Simultaneously, AI literacy has become an increasingly important learner-side construct, with contemporary frameworks spanning knowledge or awareness, practical use, critical evaluation, and ethical responsibility (Chee et al., 2025;

Han & Zhang, 2026; Ng et al., 2024; Wang et al., 2023). Direct literacy acceptance links are no longer present. Self-reported AI literacy has been related to perceived ease, usefulness, and acceptance (Schiavo et al., 2024), and recent educational studies have integrated AI literacy with acceptance and intention models (Salhab & Aboushi, 2025; Yang et al., 2025; Zhang et al., 2025; Asghar et al., 2026). More recently, Chen & Chi (2026) used a five-dimensional GenAI-literacy framework within TAM in a job-search context, and Zhao et al. (2026) identified heterogeneous AI-literacy profiles associated with AI acceptance. Therefore, the novelty question is not whether AI literacy matters for acceptance but how its multidimensional structure can be located more precisely within the acceptance mechanism in learning contexts.

A more specific measurement-to-mechanism gap must be addressed. Existing acceptance studies commonly operationalize AI literacy as a global score, enter literacy dimensions separately, examine context-specific multidimensional components, or compare heterogeneous literacy profiles. These approaches identify literacy-related relationships but do not test whether the shared variance among distinct competencies can be represented as a higher-order learner capability that relates simultaneously to perceived ease of use, perceived usefulness, and attitude. Conversely, multidimensional measurement research supports higher-order representations of AI literacy (Ng et al., 2024), and a recent TAM–IDT study modeled second-order AI literacy as an outcome of technology-related antecedents (Cao & Zheng, 2026). Less established is the reverse theoretical positioning tested here: whether awareness, usage skills, critical understanding, and ethics awareness can be represented as a common higher-order learner capability positioned upstream of the core TAM evaluations, while the established paths to behavioral intention are retained. This question is especially relevant when acceptance concerns AI-enabled technologies used for learning rather than a single branded platform or a non-learning task such as a job search.

This study addresses this gap by specifying AI literacy as a higher-order construct represented by four first-order dimensions: AI awareness, AI usage skills, AI critical understanding, and AI ethics awareness, and embedding it within an extended TAM. The model tests theory-specified associations from AI literacy to perceived ease of use, perceived usefulness, and attitude, together with standard TAM relationships, leading to behavioral intention. This study concerns students' acceptance of AI-enabled technologies used for learning, not an integrated digital learning system. Therefore, it distinguishes multidimensional capability from mere exposure: a learner may recognize AI but lack productive prompting skills, operate a tool but fail to verify plausible errors, or use AI frequently without attending to privacy and academic integrity.

This study makes three contributions. *First*, it repositions multidimensional AI literacy as a higher-order learner capability operating upstream within a TAM acceptance structure, rather than claiming that either AI literacy acceptance links or higher-order AI-literacy measurements are new. *Second*, it retains awareness, usage skills, critical understanding, and ethics awareness in the measurement architecture while estimating how their shared higher-order representation relates to ease, usefulness, and attitudes. *Third*, it evaluates this capability belief structure in a multi-institutional sample whose members reported

using several AI categories for learning purposes. The Indonesian setting is treated as an empirical boundary condition, and the multi-tool referent broadens ecological relevance while acknowledging that tool-specific acceptance processes may differ.

2 Literature review and hypothesis development

2.1 Multidimensional AI literacy as a higher-order learner capability

AI literacy has expanded from knowing what AI is to understanding what learners can do with AI and how they evaluate its output and consequences. Wang et al. (2023) validated a scale of competence in using AI, while Ng et al. (2024) operationalized affective, behavioral, cognitive, and ethical dimensions. More recent frameworks and assessments have also identified knowledge, practical use, evaluation, and ethical responsibility as recurring components, although their exact organization varies by population and purpose (Chee et al., 2025; Han & Zhang, 2026; Tadimalla & Maher, 2025). AI-integrated instruction can also develop literacy beyond simple exposure to tools (Gulen & Kucuk, 2026). This literature supports a multidimensional view rather than equating AI literacy with the frequency of use, familiarity with one application, or a single undifferentiated competence.

For the present study, four dimensions capture capabilities that are directly relevant to learning with AI: AI awareness concerns basic AI concepts, recognition of AI-enabled applications, and knowledge of academic use cases. AI usage skills involve prompting, selecting appropriate tools, and further processing AI output for academic work. A critical understanding of AI concerns judging accuracy, recognizing errors and bias, cross-checking outputs, and understanding limitations. AI ethics awareness concerns academic integrity, disclosure, privacy, and responsible use of AI. These dimensions are conceptually distinct but can operate together during authentic AI-supported learning: students recognize an appropriate use case, select and direct a tool, evaluate the resulting output, and decide whether and how that output can be used responsibly (Cheah et al., 2026; Fei, 2026; Kim et al., 2026).

Taken together, awareness provides conceptual orientation, usage skills enable effective interaction, critical understanding supports the evaluation of output quality and limitations, and ethical awareness guides appropriate boundaries of use. Their coordinated operation provides a rationale for testing a shared learner-capability layer while retaining the substantive distinctiveness of each dimension. Therefore, the present analysis tests a reflective higher-order representation in which the four first-order dimension scores are treated as manifestations of broader self-reported learner capability. Higher-order representations are empirically tractable in recent AI literacy research (Ng et al., 2024; Cao & Zheng, 2026); however, the measurement direction remains a substantive modeling choice rather than a settled ontology. A formative interpretation is also plausible because the four competencies can be viewed as complementary components that together form comprehensive literacy. The reflective specification is used here to test whether they share a common capability; it does not imply that the competencies are

interchangeable, equally important for every technology belief, or causally produced by a single underlying trait.

2.2 AI literacy and technology beliefs

Higher-order hypotheses concern shared learner capabilities rather than equal dimension-specific effects. Students with stronger AI literacy may experience fewer cognitive and procedural barriers when using AI; awareness can reduce uncertainty about what a tool can and cannot do, and usage skills support more effective prompting, tool selection, and interaction. Shahzad et al. (2024) linked ChatGPT awareness with adoption through ease- and usefulness-related beliefs; Yang et al. (2025) synthesized evidence placing AI literacy within acceptance pathways involving perceived ease of use; and Chen & Chi (2026) found that GenAI literacy was associated with perceived ease in a distinct job-search context. Prompting research further indicates that interaction patterns vary according to AI literacy levels (Kim et al., 2026). These findings support a positive association between shared AI-literacy capability and perceived ease of use, without implying that each literacy dimension contributes equally or that ease is determined by literacy.

AI literacy may also support more calibrated usefulness judgments. Awareness and usage skills can help learners match AI functions to academic tasks, while critical understanding enables them to judge accuracy, limitations, and potential bias rather than treating fluent output as inherently useful. Ethics awareness adds a further boundary condition by helping learners consider whether a technically useful action is also appropriate under the requirements of academic integrity, disclosure, and privacy. This reasoning is consistent with task technology perspectives, in which the fit between technological functions and user tasks relates to intention (Al-Mamary et al., 2024), with empirical evidence connecting AI literacy to perceived value and acceptance (Salhab & Aboushi, 2025); (Yang et al., 2025), and with recent multidimensional evidence linking GenAI literacy to perceived usefulness (Chen & Chi, 2026). Accordingly, higher-order AI-literacy capabilities are expected to be positively associated with perceived usefulness.

Competence may also be related to affective evaluations. Students who understand AI, can use it effectively, can question its outputs, and can make informed decisions about integrity, disclosure, privacy, and responsible use have a stronger basis for forming a considered attitude toward AI-supported learning. In this sense, a favorable attitude need not reflect uncritical enthusiasm; awareness and usage skills may reduce uncertainty and interaction difficulty, whereas critical understanding and ethics awareness may support confidence that remains sensitive to limitations and the appropriate boundaries of use. Wang et al. (2025) found that AI literacy was related to attitudes toward generative AI, whereas Zhang et al. (2025) showed that separate literacy dimensions could have different relationships with attitudinal and control-related constructs. Zhao et al. (2026) likewise showed that different literacy profiles are associated with varying levels of AI acceptance. The present higher-order test asks a different question: whether the shared capability underlying the four dimensions is associated with attitude after the dimensions are collectively represented.

H1

AI literacy is positively associated with the perceived ease of use of AI in learning.

H2

AI literacy is positively associated with the perceived usefulness of AI in learning.

H3

AI literacy is positively associated with students' attitudes toward using AI for learning.

2.3 Technology Acceptance Model relationships in AI-enabled learning

TAM proposes that technologies perceived as easier to use are also more likely to be judged useful because lower interaction effort can make system capabilities easier to translate into task performance (Davis, 1989). This remains plausible in AI-supported learning: a tool that is easier to learn, query, and direct may be more readily judged useful for understanding material or completing academic tasks. Recent AI acceptance studies continue to report positive relationships among ease, usefulness, attitude, and intention, while research extending TAM with learner-side attributes such as learning agility and motivation further shows that technology evaluations can vary with the characteristics learners bring to adoption (Kim & Moon, 2025; Şimşek et al., 2025; Zhao et al., 2024). These findings support retaining the core TAM structure while examining AI literacy as a distinct learner capability antecedent.

Perceived ease of use can also relate to attitude because low-friction interaction may make a technology less burdensome and more favorable to use. Zhao et al. (2024) reported positive ease–attitude and usefulness–attitude relationships for ChatGPT, and other recent AI-acceptance models likewise retain attitude as an evaluative link between technology beliefs and intention (Hazaimeh & Al-Ansi, 2024; Karan & Chakma, 2026). Retention attitudes are particularly relevant for AI because students can recognize its functional value while remaining cautious about its reliability, integrity, and institutional rules.

Therefore, perceived usefulness is expected to be positively associated with attitude and behavioral intention, while attitude is expected to have a direct association with intention. These paths were not treated as mediation tests in the present study; they retained the core TAM sequence so that the associations of the higher-order AI-literacy construct could be evaluated within an established acceptance structure (Davis, 1989; Tiwari et al., 2024; Zhao et al., 2024).

H4

Perceived ease of use is positively associated with the perceived usefulness of AI for learning.

H5

Perceived ease of use is positively associated with students' attitudes toward using AI for learning.

H6

Perceived usefulness is positively associated with students' attitudes toward using AI for learning.

H7

Perceived usefulness is positively associated with the behavioral intention to use AI for learning.

H8

Attitude toward using AI is positively associated with behavioral intention to use AI for learning purposes.

2.4 Proposed research model

Taken together, the literature positions AI literacy as a learner capability that may be associated with three proximal technology evaluations while retaining the established TAM sequence from ease and usefulness to attitude and behavioral intention. Figure 1 summarizes the resulting higher-order extension. The arrows from AI literacy to its four dimensions represent the reflective higher-order measurement specification, whereas H1-H8 represent the theory-specified structural relationships tested in the model.

<<INSERT Fig. 1**>>**

3 Method

3.1 Design and participants

A cross-sectional, multi-institutional survey was conducted to examine students' acceptance of AI-enabled technologies used for learning. The sample was criterion-based: respondents had to be active university students and had previously used at least one AI-enabled application in learning activities, so they evaluated technologies with which they had direct experience rather than hypothetical descriptions. Therefore, this study concerns a class of AI-enabled learning technologies rather than a single platform or an integrated digital learning system. Participation was voluntary and anonymous. The survey introduction explained the study purpose, use of aggregated data for academic research, the right to stop at any time without consequence, and that continuing the questionnaire would indicate consent.

The initial dataset contained 570 responses. Before model estimation, 42 cases were excluded because they exhibited complete straight-lining across all 32 measurement items (zero within-person response variance). This respondent-level rule was applied before any item-level measurements were refined. The final analytical sample consisted of 528 students enrolled at three Indonesian universities: University A

in South Sulawesi (n = 210, 39.8%), University B in East Kalimantan (n = 242, 45.8%), and University C in the Special Region of Yogyakarta (n = 76, 14.4%), including 172 males (32.6%) and 356 females (67.4%). All respondents reported prior AI use for learning; 69.9% had used AI for at least one year, 47.3% reported use three to five times per week, and 11.4% reported using it daily. Generative AI/chatbot applications were the most common category (85.0%), followed by AI translation tools (43.9%), image/video generators (40.7%), and writing assistants (31.4%) used. As students could report more than one category, these percentages were not mutually exclusive.

<<INSERT Table 1**>>**

Table 1
Distribution of participants by institution and gender

Institution	Men, n	Women, n	Total, n	% of sample
University A, South Sulawesi	101	109	210	39.8
University B, East Kalimantan	34	208	242	45.8
University C, Special Region of Yogyakarta	37	39	76	14.4
Total	172	356	528	100.0

3.2 Measures

The questionnaire was administered in Indonesian using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Appendix A provides the English translations of the retained items. AI literacy items were adapted and contextualized from established multidimensional measures and frameworks (Han & Zhang, 2026; Ng et al., 2024; Wang et al., 2023). AI awareness encompasses basic conceptual understanding, recognition of AI-enabled applications, academic use cases, and AI in the learning environment. AI usage skills assessed prompting, selecting an appropriate AI application, and further processing AI output into one's academic work. Critical understanding of AI assessed accuracy checking, recognition of errors and bias, cross-checking against other sources, and understanding AI limitations. AI ethics awareness assesses academic integrity, disclosure of AI use, data privacy, and responsible use.

The TAM constructs were perceived ease of use, perceived usefulness, attitude toward using AI, and behavioral intention to use AI. Their wording was adapted from the original TAM logic (Davis, 1989) and contextualized for AI-supported university learning in light of recent AI-acceptance research (Hazaimeh & Al-Ansi, 2024; Karan & Chakma, 2026; Tiwari et al., 2024; Zhao et al., 2024). Perceived ease of use assessed ease of learning, clarity of interaction, effort required, and overall ease of use. Perceived usefulness assessed whether AI improved learning outcomes, supported the understanding of difficult material, and was useful overall. Attitude captured liking, positive evaluation, and enjoyment of AI-assisted learning. Behavioral intention captured future use, plans for routine use, recommendations to peers, and continued use when access was available.

The instrument initially contained 32 items. After respondent screening, the measurement model diagnostics indicated localized discriminant validity overlap. Three conceptually broad items were removed as a minimal, data-informed refinement: deleting AUS1 reduced the AI awareness–AI usage skills HTMT from .939 to .896; deleting PU1 reduced the perceived ease of use–perceived usefulness HTMT from .914 to .881; and deleting ATT1 reduced the attitude–behavioral intention HTMT from .905 to .881. Each affected construct retained at least three theoretically central indicators, and no additional respondents were removed to force-fit the criteria. The final model included 29 observed indicators. Because the deletions were informed by the present data, the refined specification should be independently confirmed, rather than treated as a fully prespecified measurement model. AI literacy should also be interpreted as self-reported capability and awareness, not as an objective performance test.

3.3 Data analysis

Partial least squares structural equation modeling (PLS-SEM) was conducted using SmartPLS 4. PLS-SEM was selected because the analysis estimated a hierarchical component model and focused on the explained variance within a theory-extending structure rather than a global covariance fit, consistent with the established reporting guidelines for PLS-SEM and higher-order constructs (Hair et al., 2019; Sarstedt et al., 2019). A disjoint two-stage procedure was used because AI literacy was modeled at a higher level (Sarstedt et al., 2019). In Stage 1, AI awareness, AI usage skills, AI critical understanding, and AI ethics awareness were estimated as separate first-order reflective constructs, along with the TAM constructs. After the Stage 1 measurement model met the stated reliability and validity criteria, four latent variable scores were saved. In Stage 2, these scores served as reflective indicators of the higher-order AI-literacy construct, whereas the TAM constructs were measured using their retained original indicators. This specification tests whether the four correlated competencies share a higher-order representation; it does not establish that they are conceptually interchangeable.

Measurement evaluation considered indicator loadings, internal consistency, convergent validity, and discriminant validity. Loadings of approximately .70 or higher were treated as evidence of indicator reliability; Cronbach's alpha and composite reliability values of .70 or higher indicated adequate internal consistency; AVE values of .50 or higher indicated convergent validity; and HTMT values below .90 supported discriminant validity (Henseler et al., 2015). Structural evaluation considered the inner VIF, standardized path coefficients, bootstrap t-statistics and p-values, 95% confidence intervals, R^2 and f^2. SmartPLS bootstrapping with 5,000 resamples was used to obtain inferential statistics and confidence intervals for the estimated paths. The eight a priori structural paths were H1-H8. The PEOU → behavioral intention path was also estimated as a supplementary exploratory relationship and reported separately in this study. Because the study is cross-sectional, structural coefficients are interpreted as theory-consistent associations rather than causal effects; R^2 values describe in-sample explained variance and are not evidence of out-of-sample predictive performance.

4 Results

4.1 Descriptive results

Descriptive statistics indicated generally favorable self-reports of AI-related capabilities and technology beliefs. AI ethics awareness had the highest mean among the four literacy dimensions (M = 4.01, SD = 0.70), followed by AI critical understanding (M = 3.84, SD = 0.65), AI awareness (M = 3.81, SD = 0.64), and AI usage skills (M = 3.72, SD = 0.71). A descriptive composite of the four dimensions had a mean of 3.84 (SD = 0.59); this arithmetic summary should not be confused with the standardized latent variable scores used to estimate the Stage 2 higher-order construct. Perceived usefulness (M = 3.91, SD = 0.73), perceived ease of use (M = 3.80, SD = 0.69), and attitude (M = 3.69, SD = 0.73) were relatively high, whereas behavioral intention was lower (M = 3.48, SD = 0.75). Table 2 presents the full descriptive statistics.

Table 2
Descriptive statistics for study constructs (N = 528)

Construct	M	SD	Minimum	Maximum
AI awareness	3.81	0.64	1.00	5.00
AI usage skills	3.72	0.71	1.33	5.00
AI critical understanding	3.84	0.65	1.25	5.00
AI ethics awareness	4.01	0.70	1.00	5.00
AI literacy	3.84	0.59	1.33	5.00
Perceived ease of use	3.80	0.69	1.00	5.00
Perceived usefulness	3.91	0.73	1.00	5.00
Attitude toward using AI	3.69	0.73	1.00	5.00
Behavioral intention to use AI	3.48	0.75	1.00	5.00

<<INSERT Table 2**>>**

4.2 Stage 1: First-order measurement model

All retained indicators loaded above .70, ranging from .740 (ACU1) to .889 (PU4). Cronbach's alpha ranged from .771 to .888, composite reliability from .854 to .922, and average variance extracted (AVE) from .593 to .778. The full Stage 1 HTMT matrix (Appendix B) remained below .90 after measurement refinement, with the highest value being .896 for AI awareness and usage skills. Under the stated criteria, the retained first-order constructs demonstrated adequate indicator reliability, internal consistency, convergent validity, and discriminant validity for the Stage 2 analysis. Table 3 summarizes the reliability and convergent validity.

Table 3
Stage 1: Reliability and convergent-validity results

Construct	Retained indicators	Loading range	α	CR	AVE
AI awareness	AIA1–AIA4	.775–.826	.813	.877	.641
AI usage skills	AUS2–AUS4	.821–.852	.792	.878	.706
AI critical understanding	ACU1–ACU4	.740–.794	.771	.854	.593
AI ethics awareness	AEA1–AEA4	.825–.879	.876	.915	.729
Perceived ease of use	PEOU1–PEOU4	.760–.874	.855	.902	.698
Perceived usefulness	PU2–PU4	.868–.889	.857	.913	.778
Attitude toward using AI	ATT2–ATT4	.868–.886	.849	.908	.768
Behavioral intention	BI1–BI4	.830–.884	.888	.922	.748

<<INSERT Table 3**>>**

4.3 Stage 2: Higher-order measurement model

The four Stage 1 construct scores loaded strongly on the higher-order AI-literacy construct: AI awareness = .884, AI critical understanding = .874, AI usage skills = .874, and AI ethics awareness = .860 (all $p < .001$). The higher-order representation also showed internal consistency (α = .896; CR = .928) and convergent validity (AVE = .762). The narrow loading range indicates that each dimension was strongly related to the common reflective representation; it does not show that the dimensions are substantively equivalent or equally important for specific learning outcomes.

<<INSERT Table 4**>>**

Table 4
Higher-order AI-literacy loadings in Stage 2

AI-literacy dimension	Loading	t	p
AI awareness	.884	75.796	< .001
AI critical understanding	.874	62.492	< .001
AI ethics awareness	.860	58.470	< .001
AI usage skills	.874	82.153	< .001

Discriminant validity remained within the prespecified HTMT threshold in Stage 2. The HTMT values were .800 for AI literacy attitude, .726 for AI literacy behavioral intention, .880 for AI literacy perceived ease of use, and .853 for AI literacy perceived usefulness. Among the TAM constructs, the largest values were .881 for attitude–behavioral intention and .881 for perceived ease of use–perceived usefulness

(Table 5). Because several values were close to .90, the constructs should be interpreted as empirically distinguishable but conceptually related, rather than sharply separated.

Table 5
HTMT matrix for the final Stage 2 measurement model

Construct	AI literacy	Attitude	Behavioral intention	PEOU	PU
AI literacy	—				
Attitude	.800	—			
Behavioral intention	.726	.881	—		
PEOU	.880	.812	.801	—	
PU	.853	.824	.759	.881	—

<<INSERT Table 5**>>**

4.4 Structural model and hypothesis tests

The inner VIF values for the eight theory-specified paths ranged from 1.000 to 3.068. All eight theory-specified associations were positive and statistically significant at the 5% level. Table 6 presents the standardized coefficients, bootstrap statistics, confidence intervals, f^2 values, and hypothesis decisions; Table 7 presents the R^2 and adjusted R^2. The estimated model accounted for 60.3%, 64.1%, 58.4%, and 65.6% of the variance in perceived ease of use, perceived usefulness, 58.4% in attitude, and 65.6% in behavioral intention, respectively. These R^2 values describe the in-sample explained variance and are not interpreted as out-of-sample predictive accuracy.

Table 6
Structural paths, effect sizes, collinearity, and hypothesis testing

Hyph	Path	β	t	p	95% CI	f²	VIF	Decision
H1	AI literacy → PEOU	.777	36.911	< .001	[.735, .817]	1.519	1.000	Supported
H2	AI literacy → PU	.406	8.612	< .001	[.312, .499]	.182	2.519	Supported
H3	AI literacy → Attitude	.276	4.841	< .001	[.166, .388]	.062	2.977	Supported
H4	PEOU → PU	.444	9.543	< .001	[.354, .536]	.218	2.519	Supported
H5	PEOU → Attitude	.242	4.237	< .001	[.134, .356]	.046	3.068	Supported
H6	PU → Attitude	.315	5.308	< .001	[.199, .429]	.086	2.785	Supported
H7	PU → Behavioral intention	.110	2.203	.028	[.014, .205]	.013	2.755	Supported
H8	Attitude → Behavioral intention	.510	11.808	< .001	[.427, .598]	.333	2.265	Supported

Table 7
Explained variance in endogenous constructs

Endogenous construct	R^2	Adjusted R^2
Perceived ease of use	.603	.602
Perceived usefulness	.641	.640
Attitude toward using AI	.584	.582
Behavioral intention to use AI	.656	.654

<<INSERT Table 6**>>**

<<INSERT Table 7**>>**

AI literacy showed the largest association with perceived ease of use (β = .777, p < .001; f^2 = 1.519), followed by perceived usefulness (β = .406, p < .001; f^2 = .182) and attitude (β = .276, p < .001; f^2 = .062). Within TAM, perceived ease of use was associated with perceived usefulness (β = .444, p < .001; f^2 = .218) and attitude (β = .242, p < .001; f^2 = .046), whereas perceived usefulness was associated with attitude (β = .315, p < .001; f^2 = .086). Attitude had the largest direct association with behavioral intention (β = .510, p < .001; f^2 = .333). The direct perceived usefulness–intention path was statistically detectable

but small (β = .110, p = .028; f^2 = .013), and these estimates describe the conditional associations in the specified model and should not be interpreted as causal effects.

4.5 Supplementary exploratory analysis

A supplementary direct path from perceived ease of use to behavioral intention was positive (β = .266, t = 6.137, p < .001, 95% CI [.182, .349], f^2 = .077, and VIF = 2.679). Because this relationship was not specified among H1–H8, it was exploratory rather than a confirmatory relationship. The H1–H8 coefficients were estimated in the same Stage 2 model and are therefore conditional on the inclusion of this additional path; a strictly pre-specified H1–H8 model was not separately estimated in the present analysis. As illustrated in Fig. 2, the supplementary path is represented by a dashed line to visually distinguish it from the theory-specified relationships,

<<INSERT Fig. 2**>>**

5 Discussion

This study tested whether four related AI-literacy dimensions could be represented as higher-order learner capabilities within students' acceptance of AI-enabled learning technologies. The measurement results supported the specified reflective representation, and the structural model linked that shared capability to perceived ease of use, perceived usefulness, and attitude, while retaining established TAM relationships. This pattern converges with prior evidence that GenAI literacy relates to acceptance-related beliefs and intentions (Schiavo et al., 2024; Salhab & Aboushi, 2025; Yang et al., 2025; Zhang et al., 2025) and with newer work connecting multidimensional GenAI literacy to TAM beliefs in a job-search context (Chen & Chi (2026) and AI-literacy profiles to AI acceptance (Zhao et al., 2026). The present contribution is therefore narrower and more specific: unlike models using global literacy scores, separate dimensions, context-specific component weights, latent profiles, or positioning AI literacy as a downstream outcome (Cao & Zheng, 2026), this study tests a shared reflective higher-order capability positioned upstream of three proximal TAM evaluations in AI-supported learning.

The strongest association was between AI literacy and the perceived ease of use of AI. One plausible interpretation is that ease in AI-supported learning is partly relational rather than purely interface-based. The same AI tool may feel more manageable to a learner who understands its affordances, can formulate usable prompts, selects an appropriate application, and recognizes when an output requires correction. This interpretation is consistent with evidence that AI literacy relates to ease-related acceptance beliefs (Schiavo et al., 2024; Yang et al., 2025), prompt patterns differ by AI-literacy level (Kim et al., 2026), and learner-side adaptability is associated with perceived ease of generative-AI use (Şimşek et al., 2025). Nevertheless, this should be treated as an interpretation, not a demonstrated mechanism. Both AI literacy and perceived ease of use were measured by self-report in the same survey, and their Stage 2 HTMT value was .880, below the stated threshold but sufficiently high to indicate substantial conceptual proximity. Therefore, the unusually large f^2 for the AI-literacy ease path may reflect both a substantive learner capability relationship and shared evaluative content or method

variance. Longitudinal, experimental, or performance-based designs are required to separate these possibilities from each other.

AI literacy was also moderately associated with perceived usefulness. This result is theoretically plausible because usefulness is not self-evident for generative and other AI tools; learners must identify where a tool fits a task and distinguish genuine assistance from plausible but unreliable output. This pattern aligns with task–technology reasoning (Al-Mamary et al., 2024), and Yang et al. (2025) synthesis, which placed AI literacy alongside usefulness in educational-AI intention pathways. However, the present study does not show that literacy causes students to perceive AI as more useful. A reverse or reciprocal interpretation is also possible: repeated experiences of useful AI may contribute to perceived competence and AI literacy. The cross-sectional design of the study cannot establish the order.

The direct association between AI literacy and attitude was smaller than the association between ease and usefulness. This distinction is informative because it suggests that a shared literacy capability is not equivalent to enthusiasm for using AI technology. Zhang et al. (2025) found that separate AI-literacy dimensions can relate differently to attitude and other adoption constructs, whereas the present higher-order analysis captures only what the four dimensions share. Similar higher-order loadings should not be interpreted as evidence that awareness, usage skills, critical understanding, and ethics have identical attitudinal effects. Dimension-specific structural comparisons would require a different model. The relatively high ethics-awareness mean is compatible with a more calibrated form of acceptance, in which positive evaluations coexist with caution regarding integrity, privacy, and social responsibility.

The internal TAM pattern warrants further attention. Perceived ease of use was associated with usefulness and attitude, and perceived usefulness was associated with attitude, consistent with recent AI-acceptance studies (Hazaimeh & Al-Ansi, 2024; Kim & Moon, 2025; Zhao et al., 2024). However, the direct usefulness intention coefficient was small ($\beta = .110$; $f^2 = .013$), whereas attitude showed a much larger direct association with intention ($\beta = .510$; $f^2 = .333$). This does not establish mediation because the indirect effects were not tested in this study. This indicates that within this conditional model, usefulness contributed little unique direct variance to intention after the other predictors were included, whereas attitude retained a stronger association. For AI-enabled learning, students may regard a technology as useful without necessarily intending to use it routinely or continuously when concerns about assessment rules, privacy, accuracy, or appropriate task boundaries remain.

This interpretation is compatible with responsible-AI scholarship, which cautions against treating adoption frequency as a sufficient indicator of educational value (Chang & Wong, 2025; Kofinas et al., 2025; Ritzhaupt et al., 2026). By retaining critical understanding and ethics awareness within AI literacy, the model frames acceptance as an informed willingness to use AI where appropriate, rather than maximal willingness to use it. This framing is particularly relevant to digital learning technology because implementation decisions involve not only access and usability but also learners' capacity to evaluate outputs, disclose assistance, protect data, and recognize tasks for which AI should not substitute for

independent work. The present data support the relevance of these capabilities to acceptance-related beliefs but do not demonstrate that literacy training will increase responsible use.

Finally, the supplementary PEOU intention path was positive and significant, suggesting a possible residual association between interaction effort and intention beyond attitude and usefulness. This should not be elevated to a theoretical finding because the path was not pre-specified, and the H1–H8 coefficients were estimated in the same model that contained it. A future confirmatory study should compare a strictly prespecified H1–H8 model with an explicitly extended model, ideally using an independent sample and out-of-sample predictive assessment. Such replication would clarify whether the additional direct path is stable across AI tools, tasks, disciplines and learner groups.

6 Implications

6.1 Theoretical contributions

The theoretical contribution should be understood as an integration of measurement architecture and acceptance mechanism, not as the first attempt to connect AI literacy with technology acceptance or to represent AI literacy in multiple dimensions. Recent studies have already shown literacy–acceptance links using global scores, separate dimensions, integrated acceptance frameworks, context-specific multidimensional components, and latent profiles (Schiavo et al., 2024; Salhab & Aboushi, 2025; Yang et al., 2025; Zhang et al., 2025; Asghar et al., 2026; Chen & Chi, 2026; Zhao et al., 2026), while second-order AI-literacy modeling has also been used in recent work (Cao & Zheng, 2026). The added contribution here is the conjunction of these ideas: awareness, usage skills, critical understanding, and ethics awareness are represented by a common reflective higher-order capability, and that shared capability is positioned upstream of perceived ease of use, perceived usefulness, and attitude within the TAM structure focused on AI-enabled learning.

The second contribution is conceptual in nature. The model places learner capability alongside technology beliefs, without merging the two. TAM continues to describe how students evaluate ease and usefulness, while the higher-order AI-literacy construct represents what learners report knowing and being able to do when interacting with AI. The strong association with literacy ease suggests that perceived usability in AI contexts may partly depend on the learner–technology relationship, although the cross-sectional and self-reported design prevents stronger causal or process claims.

The third contribution is to keep the responsible-use capability visible in acceptance research. Ethics awareness, critical understanding, and practical skills are represented within the same broader capability, rather than treating acceptance as a purely efficiency-oriented outcome. This architecture does not prove that ethical awareness causes more appropriate use, nor does it imply that ethics are exhausted by the four self-report items. It provides a measurable route for examining whether responsible-use capabilities remain connected to acceptance-related evaluations as AI becomes more deeply embedded in learning processes.

The multi-institutional Indonesian sample and inclusion of several AI application categories provide a context for testing this architecture beyond a single branded tool. The breadth is useful but should be interpreted as a boundary condition rather than universal evidence. Tool-specific, discipline-specific, and cross-national tests are needed before structural patterns can be generalized.

6.2 Practical implications

For universities and designers of digital learning environments, the findings suggest that implementation evaluation should consider learner capability alongside access, usability, and perceived usefulness. The associations do not show that literacy training will cause greater acceptance, but they support treating AI literacy as a relevant readiness condition when institutions introduce or scale AI-enabled learning technologies for students. Capability development can address four complementary strands: conceptual awareness of AI and its task affordances; practical skills, such as prompting and tool selection; critical practices for checking accuracy, bias, evidence, and limitations; and ethical practices concerning integrity, disclosure, privacy, and responsibility.

These strands can be embedded in authentic digital learning activities rather than being delivered only as standalone policy guidance. For example, students can be asked to compare outputs from different prompts, verify claims against scholarly sources, document why a prompt was revised, identify uncertainty or bias, and justify when AI assistance is or is not appropriate to use. Such tasks are consistent with work emphasizing purposeful student–AI interactions and reflective human–AI partnerships (Dalsgaard & Prilop, 2026; Fei, 2026; Kim et al., 2026). The aim is not to teach prompting as a purely technical skill but to connect interaction quality with verification and judgment.

Ethical capability can also be operationalized through assessment designs. Courses can require transparent disclosure of AI assistance, documentation of verification decisions, reflection on data privacy, and explanations of how the final academic product differs from the raw AI output. Reviews of AI ethics curricula show that translating broad principles into practice remains difficult (Chang & Wong, 2025), and assessment-level routines provide a way to make those principles observable. These practices should be evaluated for their learning quality and integrity rather than being assumed to be effective.

Therefore, the comparatively moderate behavioral intention mean should not be treated as a deficit to be maximized. Appropriate digital learning design may legitimately support selective use; for example, students may choose not to use AI when independent practice, privacy, assessment validity, or disciplinary norms render assistance as unsuitable. A more defensible institutional objective is purposeful, justified, and transparent use supported by adequate learner capability rather than universal or continuous adoption.

7 Limitations and future research

Several limitations should be considered when interpreting the findings of this study. *First*, the cross-sectional design does not establish temporal or causal ordering; therefore, the structural paths should be interpreted as theory-consistent associations rather than causal effects. *Second*, AI literacy and TAM constructs were measured using self-reports within the same survey, which may have introduced response bias and common method variance. Future studies should incorporate performance-based tasks, source verification exercises, or behavioral trace data. *Third*, the higher-order specification of AI literacy represents a plausible conceptualization rather than a definitive ontology; alternative reflective and formative models should be compared and tested for measurement invariance. *Fourth*, the criterion-based sample was drawn from three Indonesian universities with unequal institutional representation and a predominantly female sample, limiting broader generalizations. *Fifth*, respondents evaluated different types of AI-enabled learning tools, creating potential referent heterogeneity across various technologies and tasks. Finally, three indicators were removed during measurement refinement, and an exploratory PEOU-intention path was estimated alongside the hypothesized model. Future research should validate the refined 29-item instrument in independent samples, use pre-specified structural models, assess out-of-sample prediction, and incorporate actual-use or behavioral outcomes.

8 Conclusion

Students' acceptance of AI-enabled learning technologies was associated not only with perceived ease, usefulness, and attitude but also with the multidimensional capabilities they reported bringing to their interaction with AI. In this three-university sample, awareness, usage skills, critical understanding, and ethics awareness formed a strong, reflective, higher-order AI literacy representation. This shared capability was most strongly associated with perceived ease of use and was also associated with perceived usefulness and attitude; within TAM, attitude retained the largest direct association with behavioral intention. Therefore, this study supports examining learner capability alongside technology beliefs when studying AI adoption in digital learning. It does not establish that increasing AI literacy causes acceptance or responsible use. For research and practice, the more defensible implication is to evaluate whether learners can understand, operate, question, and use AI appropriately as institutions implement AI-enabled learning technology. Longitudinal, experimental, tool-specific, and performance-based studies are needed to test the order and generalizability of these relationships.

Declarations

Ethical Approval and Consent to Participate

This study involved human participants and employed a non-interventional questionnaire-based design in an educational setting. Given the minimal-risk nature of the research, formal ethical approval was not sought prior to data collection, and no institutional ethics committee or Institutional Review Board (IRB) reviewed this study. Participation was voluntary, and informed consent was obtained from all participants prior to the data collection. Participants' confidentiality and privacy were maintained throughout the study.

Funding

This work was supported by the Institute for Research and Community Service (LPPM), Universitas Negeri Makassar, Indonesia, through the Faculty of Engineering Internal PNBP Research Grant (award numbers: 328/DST/UN36/HK/2026; 669/DST/UN36.12/TU/2026).

Conflict of interest

The authors declare no conflicts of interest for this study

Data availability

The data are available upon reasonable request.

Declaration of AI-assisted writing

The authors used ChatGPT (OpenAI) alone for AI-assisted language editing to improve the grammar, readability, and clarity of this manuscript. The tool was not used to generate research questions, hypotheses, data, analyses, results, or conclusions. All AI-assisted edits were reviewed and approved by the authors, who are fully responsible for the content of the manuscript.

Author Contribution

R.D.M. contributed to conceptualization, research design, methodology, formal analysis, writing the original draft, and critical revision of the manuscript. F.B. contributed to investigation, data collection, data curation, and interpretation of findings. M. contributed to investigation, validation, literature review, and critical revision of the manuscript. O.H. contributed to data collection, visualization, and review and editing of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Figures

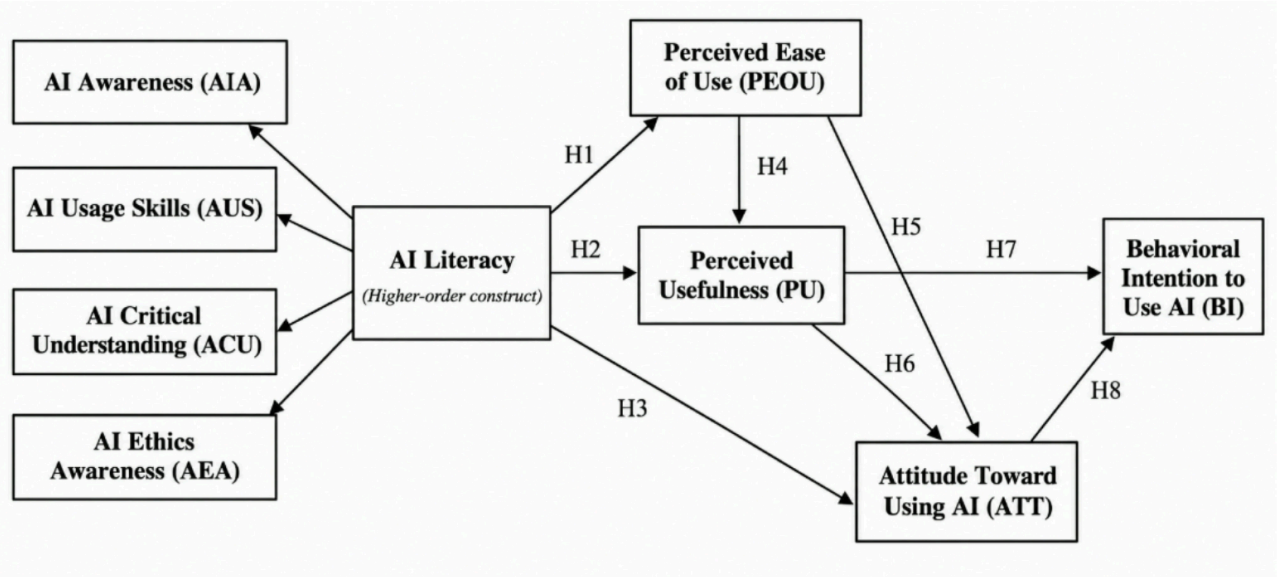


Figure 1

Research model

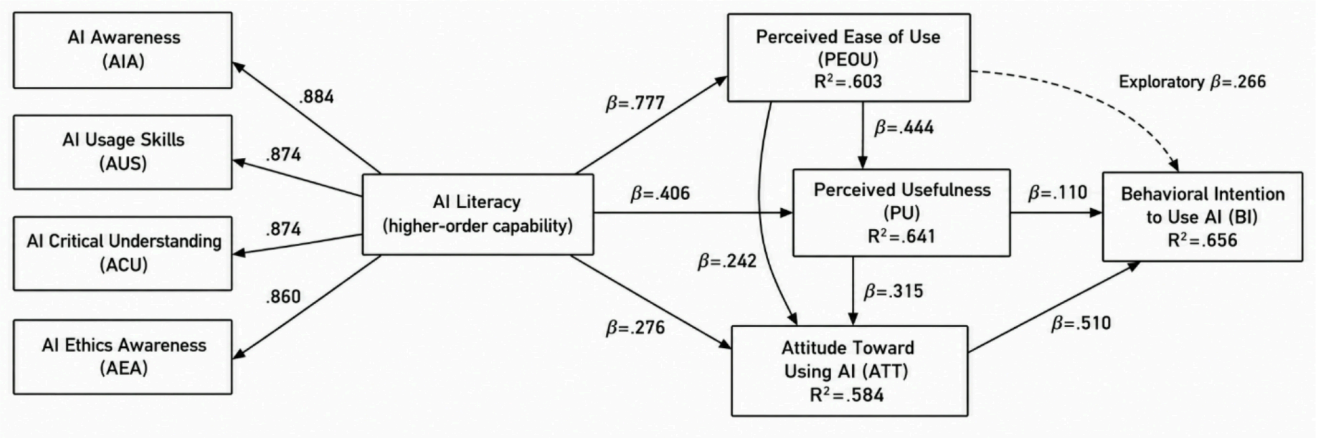


Figure 2

Stage 2 structural results with standardized coefficients and R^2 values

Supplementary Files

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- SupplementaryFileAppendixAB.docx