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Student Readiness for AI in Business: Roles of Literacy, Attitude, and Practical Engagement

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ABSTRACT

Purpose: *This study investigates the determinants of student readiness for artificial intelligence (AI) integration in business education, emphasizing the roles of AI literacy, affective attitude, and practical engagement. The research addresses the increasing demand for future business professionals equipped to operate in AI-enhanced environments.*
Methodology: *A quantitative approach was employed using survey data from 177 undergraduate students in the Greater Jakarta area. Constructs were measured through validated instruments and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine both direct and mediated relationships among variables.*
Findings: *The results show that AI literacy and affective attitude have significant direct effects on AI readiness. Practical engagement contributes to readiness indirectly through affective attitude. Affective attitude is the strongest direct predictor of readiness and significantly mediates the effects of AI literacy and practical engagement.*
Conclusion: *The findings suggest that enhancing AI readiness requires a holistic educational framework integrating conceptual knowledge, experiential exposure, and emotional receptivity. Curriculum designers should focus on affective learning strategies alongside technical training to foster a workforce capable of navigating AI-driven business contexts.*

Keywords: *AI literacy; Affective attitude; Practical engagement; Business education; Student readiness.*

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BACKGROUND

Artificial intelligence is becoming a core capability in contemporary business functions, including analytics, customer engagement, operations, and decision support. The World Economic Forum identifies AI and big data among the fastest-growing skill domains, while UNESCO emphasizes that higher education should develop both technical capability and human-centred, ethical competence in the use of generative AI. In Indonesia, expanding internet access and the development of a national AI policy agenda increase the relevance of examining whether university students are prepared to use AI responsibly and productively in future business settings (Chan & Hu, 2023; Ganguli, 2025).

Readiness for AI is multidimensional. AI literacy enables students to understand AI concepts, applications, limitations, and ethical risks. Affective attitude reflects optimism, confidence, perceived relevance, and comfort when working with AI. Practical engagement provides opportunities to test, evaluate, and apply AI tools in authentic tasks. Prior studies generally support the importance of these factors, but they often examine them separately, focus on non-business disciplines, or emphasize intention to use rather than readiness for applied business practice (Falebita & Kok, 2025; Wu & Qin, 2025).

This fragmentation creates two unresolved issues. First, the relative contribution of literacy, affect, and practical engagement remains unclear when the three are assessed within one structural model. Second, the mechanism through which knowledge and experience become readiness has received limited empirical attention. Affective attitude may serve as a psychological pathway that converts cognitive competence and practical exposure into willingness and confidence to use AI in business contexts (Bati et al., 2024; Southworth et al., 2023; You et al., 2024).

Accordingly, this study develops a parsimonious model grounded primarily in the Technology Acceptance Model (TAM) and experiential learning theory. TAM explains why favourable evaluations of technology support adoption-related outcomes, whereas experiential learning theory explains how direct interaction, reflection, and application develop competence and confidence. The model positions AI literacy as a cognitive antecedent, practical engagement as an experiential antecedent, affective attitude as an affective mechanism, and AI readiness as the outcome. This theoretical integration refines existing readiness and adoption models by explicitly testing both direct and mediated pathways among these dimensions in business education.

Research Questions

1. How do AI literacy, affective attitude, and practical engagement contribute to undergraduate students' readiness to use AI in business contexts?
2. To what extent does affective attitude mediate the effects of AI literacy and practical engagement on AI readiness?

Research Objectives

1. To estimate the direct and indirect effects of AI literacy, affective attitude, and practical engagement on student AI readiness.
2. To evaluate the mediating role of affective attitude in the relationships between AI literacy, practical engagement, and AI readiness.
3. To derive evidence-based educational implications for AI-related curriculum design in business education.

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LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Theoretical Positioning and Construct Mapping

The proposed model uses two complementary theoretical foundations. TAM explains how favourable evaluations of a technology support acceptance and readiness, whereas experiential learning theory explains how direct experience and reflective application shape competence and confidence. Rather than treating these theories as parallel descriptions, the model assigns each construct a specific theoretical role: AI literacy represents cognitive capability; practical engagement represents experiential exposure; affective attitude represents evaluative and emotional receptivity; and AI readiness represents preparedness to use AI in future business practice (Chiu et al., 2024).

The model therefore extends conventional technology-adoption research in two ways. First, it moves beyond perceived usefulness and ease of use by incorporating domain-specific literacy and practical engagement as antecedents. Second, it specifies affective attitude as a mediating mechanism through which knowledge and experience are translated into readiness. This positioning provides a more parsimonious cognitive–affective–experiential explanation of AI readiness without introducing theories that are not directly tested in the empirical model.

AI Literacy, Affective Attitude, and AI Readiness

AI literacy refers to the ability to understand AI concepts, recognize business applications, evaluate limitations, and interpret AI-supported outputs. Literacy can enhance readiness directly because informed students are better able to judge when and how AI should be used. However, knowledge may not be sufficient when students perceive AI as threatening, irrelevant, or difficult to control. Research has consequently shown that attitudes, confidence, and perceived relevance can strengthen or weaken the translation of AI knowledge into adoption-related outcomes (Dai et al., 2020; Falebita & Kok, 2025; You et al., 2024).

Within TAM, affective attitude captures a favourable or unfavourable evaluation of using AI. Students who are optimistic about AI, comfortable collaborating with AI-based systems, and motivated to continue learning are more likely to consider themselves prepared for AI-enabled work. AI literacy is therefore expected to improve readiness directly and indirectly by supporting a more informed and favourable attitude.

Practical Engagement and Experiential Learning

Experiential learning theory proposes that competence develops through concrete experience, reflection, conceptualization, and active experimentation. In AI education, practical engagement includes using AI tools, completing AI-assisted assignments, evaluating generated outputs, and applying AI in simulations or projects. Such experiences can reduce uncertainty, reveal limitations, and help students form more realistic evaluations of AI (Chiu et al., 2024; Kong et al., 2021).

Empirical research across business communication, health education, and broader educational settings indicates that structured exposure to AI is associated with greater familiarity, confidence, and readiness (DeVasto & Palmer, 2024; Li et al., 2024; Yalcinkaya et al., 2024). Nevertheless, exposure may remain superficial when it is limited to unstructured tool use. The theoretical expectation is therefore not merely that engagement increases readiness, but that engagement first shapes affective attitude, which subsequently supports readiness.

Integrated Model and Hypotheses

The integrated model specifies four core relationships. First, AI literacy is expected to improve affective attitude because understanding AI reduces ambiguity and supports more realistic evaluations. Second, AI literacy is expected to improve readiness directly by increasing

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students' capacity to recognize and apply AI in business tasks. Third, practical engagement is expected to strengthen affective attitude by providing concrete evidence of AI's usefulness and limitations. Fourth, affective attitude is expected to increase readiness because confidence, optimism, and perceived relevance support preparedness for future use.
H1: AI literacy has a positive effect on affective attitude toward AI.
H2: AI literacy has a positive direct effect on AI readiness.
H3: Practical engagement has a positive effect on affective attitude toward AI.
H4: Affective attitude has a positive effect on AI readiness.
H5: Affective attitude mediates the relationship between AI literacy and AI readiness.
H6: Affective attitude mediates the relationship between practical engagement and AI readiness.

METHOD

Research Methodology

This study employs a quantitative research design to examine the influence of AI literacy, affective attitude, and practical engagement on students' readiness to adopt artificial intelligence (AI) in business contexts. A quantitative approach was chosen for its ability to capture measurable relationships, validate theoretical models, and support empirical generalization.

Research Design and Sampling

The target population comprised undergraduate students enrolled at universities in the Greater Jakarta area. Data were obtained through an online questionnaire distributed from 14 to 21 July 2025. Participation was voluntary, and 177 usable responses were included. Because respondents self-selected into an online survey and no complete sampling frame with known selection probabilities was used, the procedure is more accurately classified as non-probability voluntary-response sampling rather than simple random sampling. Accordingly, statistical inference is restricted to respondents with characteristics similar to those represented in the sample.

Instrumentation and Data Collection

Data were collected through a structured online questionnaire distributed between July 14–21, 2025. The instrument comprised five sections: demographics, AI literacy, affective attitude, practical engagement with AI tools, and readiness to adopt AI. Items were measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Data Analysis Techniques

PLS-SEM was performed in SmartPLS 4. The reflective measurement model was evaluated using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity. The structural model was assessed using collinearity diagnostics, path coefficients, 5,000-subsample bootstrapping, coefficients of determination (R^2), effect sizes where available, and Stone–Geisser predictive relevance (Q^2). A sensitivity analysis for a multiple-regression approximation with two predictors, $\alpha = 0.05$, power = 0.80, and n = 177 indicates that the sample can detect an effect of approximately $f^2 = 0.056$; thus, it is adequate for small-to-moderate structural effects, although it does not remove limitations arising from non-probability sampling.

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RESULT AND DISCUSSION

Result

1. Demographic Profile of Respondents

The sample comprised 177 undergraduate students from universities in Greater Jakarta and included a broad range of academic programs. Table 1 reports the ten most frequently represented programs. Because many programs contributed only a small number of respondents, the distribution should be interpreted as heterogeneous rather than statistically representative of all business students in the region.

Table 1. Distribution of Respondents by Program of Study
(Top 10 most common programs shown)

No	Program of Study	Number of Respondents
1	Accounting	9
2	Management	8
3	Communication Studies	8
4	Psychology	7
5	Law	6
6	Information Systems	5
7	Islamic Economics	5
8	Nursing	5
9	Education Administration	4
10	International Relations	4

In terms of academic progression, a majority of respondents (approximately 64%) were in their second and third years of study. This distribution is advantageous as it captures students who are transitioning from theoretical coursework to more applied learning, thus providing a balanced view of conceptual readiness and practical engagement with AI technologies. *(see Table 2)*

Table 2. Distribution of Respondents by Academic Level

No	Year Level	Number of Respondents
1	Second Year	81
2	Third Year	33
3	First Year	27
4	Sixth Year or More	25
5	Fourth Year	8
6	Fifth Year	3

These demographic variations strengthen the structural model by ensuring that insights derived from AI readiness are not confined to a narrow academic or experiential cohort, but rather reflect broader student sentiments applicable across business-oriented education.

2. Measurement Model Validation

The reflective measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity in accordance with established PLS-SEM criteria.

2.1 Convergent Validity

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Outer loadings for all indicators exceeded the 0.70 threshold after the exclusion of a few underperforming items (P1, P2, and AF4), thus confirming that retained indicators were strongly associated with their respective constructs. *(See Table 3)*

Table 3. First *Outer Loading*

Code	Indicator Construct	Outer Loading	SD	D	N	A	SA
AD1	I feel ready to integrate AI into my future work.	0.827	2	17	86	57	14
AD2	I am confident in adapting to new AI technologies.	0.820	3	5	74	73	21
AD3	I believe my skills are sufficient to compete in an AI-driven job market.	0.810	3	13	66	71	23
AD4	I am motivated to continue learning AI in a business context.	0.884	2	12	68	76	18
AD5	I am capable of making business decisions based on AI-generated insights.	0.838	3	14	71	71	17
AD6	I am ready to collaborate in teams that actively use AI technology.	0.873	2	10	73	73	18
AD7	I am willing to upgrade my skills to remain relevant in an AI-powered workforce.	0,860	3	8	58	83	24
AD8	I understand the importance of AI for the sustainability of my future career.	0,862	4	8	60	81	23
AF1	I believe that AI will create new opportunities in the workforce.	0,736	4	9	62	71	30
AF2	I feel optimistic about the use of AI in business.	0,804	3	9	80	66	18
AF3	I believe AI can improve work efficiency and productivity.	0,793	3	3	54	88	28
AF4	I do not feel threatened by the presence of AI in my future workplace.	0,674*	**11**	**30**	**74**	**43**	**18**
AF5	I think students should learn about AI early on.	0,749	4	14	67	60	31
AF6	I feel comfortable working alongside AI-based systems.	0,834	4	9	83	63	17
AF7	I believe AI will enhance my decision-making capabilities in business.	0,779	4	10	67	74	21
AF8	I believe AI can support ethical principles in business.	0,859	3	13	84	61	15
L1	I know the basic definition of artificial intelligence (AI).	0,750	2	1	48	97	28
L2	I understand the fundamental workings of AI technology (e.g., machine learning).	0,780	3	8	56	87	22
L3	I can differentiate between AI and other digital technologies.	0,822	3	3	44	88	38
L4	I am aware of various AI applications in business.	0,809	5	16	65	64	26
L5	I understand the impact of AI on company operations and strategy.	0,841	3	9	49	87	28
L6	I can explain real-world examples of AI use in business processes.	0,799	6	14	55	70	32
L7	I understand the risks and limitations of AI in a business context.	0,858	5	8	51	87	26
L8	I can explain how AI is used in decision-making.	0,799	3	12	54	80	28
P1	I have attended training or courses on AI technology.	0,555*	30	60	49	29	8
P2	I have used AI-based tools or applications (e.g., ChatGPT, Midjourney).	0,638*	2	6	26	89	53
P3	I have completed academic tasks or projects involving AI.	0,738	4	6	39	96	31

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Code	Indicator Construct	Outer Loading	SD	D	N	A	SA
P4	I have experience running business simulations assisted by AI technology.	0,787	13	31	65	52	15
P5	I actively seek information and educational content about AI in business.	0,795	8	21	64	62	21
P6	I am interested in trying AI technology in my business or academic activities.	0,801	3	5	65	75	28
P7	I have an account or access to cloud-based AI platforms (e.g., Google AI, IBM Watson).	0,756	12	30	66	50	18
P8	I am used to critically and reflectively analyzing AI-generated outputs.	0,770	4	14	69	72	17

*Indicators marked with an asterisk were removed because their loadings were below 0.70.
* Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), and Strongly Agree (SA).
Source: Processed Primary Data

After indicators P1, P2, and AF4 were removed because of their comparatively low outer loadings, the measurement model was re-estimated. The results showed that all constructs demonstrated adequate convergent validity, with all remaining items showing significant loadings ($p < 0.001$).

2.2 Reliability

Cronbach's alpha ranged from 0.876 to 0.944, and composite reliability ranged from 0.906 to 0.953. These values exceed the commonly used 0.70 threshold and indicate satisfactory internal consistency. Because reliability coefficients above 0.95 may suggest item redundancy, the value of 0.953 for AI readiness should be interpreted together with the breadth and content of its indicators. *(see Table 4)*

Table 4. Reliability and Discriminant Validity Tests (Fornell-Larcker Criterion)

Construct	Cronbach's Alpha	Composite Reliability	AVE	√AVE	Affective Attitude	AI Literacy	Practical Engagement	Readiness to Adopt AI
Affective Attitude	0.904	0.924	0.636	0.797	0.797	0.576	0.713	0.660
AI Literacy	0.924	0.938	0.653	0.808	0.576	0.808	0.548	0.563
Practical Engagement	0.876	0.906	0.617	0.785	0.713	0.548	0.785	0.569
Readiness to Adopt AI	0.944	0.953	0.717	0.847	0.660	0.563	0.569	0.847

Source: Processed Primary Data

2.3 Average Variance Extracted (AVE)

The AVE values for all constructs were above 0.50, indicating that the latent constructs explain more than half of the variance in their respective indicators. This reinforces the reliability of the scales and their conceptual cohesion. *(see Table 4)*

2.4 Discriminant Validity

Using the Fornell-Larcker criterion, the square root of AVE for each construct exceeded the correlations between constructs. This provides evidence of discriminant validity, suggesting that each latent variable captures a distinct concept not explained by others. Therefore, multicollinearity concerns were ruled out, and the model is structurally sound for further evaluation. *(see Table 4)*

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3. Structural Model Evaluation

The structural model was evaluated to determine its empirical adequacy and the extent to which the hypothesized relationships among constructs were supported by the data. Two key fit indices were utilized in this analysis: the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI), both widely accepted within Partial Least Squares Structural Equation Modeling (PLS-SEM) frameworks. *(see Table 5)*

Table 5. Model Fit

	Saturated model	Estimated model
SRMR	0.066	0.067
NFI	0.761	0.761

The SRMR values for both the saturated (0.066) and estimated (0.067) models were well below the threshold of 0.08, indicating a satisfactory level of approximation between the observed and predicted correlations. Moreover, the NFI value of 0.761 exceeded the benchmark of 0.70, further confirming an acceptable fit between the proposed structural model and the empirical data.

These results validate the model's structural integrity and suggest that the latent constructs and their interrelationships are appropriately specified. The model is thus deemed suitable for hypothesis testing and interpretation of path coefficients.

Table 6. Predictive Power

Endogenous Construct	R^2	R^2 Adjusted	Q^2 (=1-SSE/SSO)
Affective	0.557	0.552	0.341
Readiness Adopt	0.486	0.480	0.341

In terms of explained variance, the coefficient of determination (R^2) for the latent variable Affective Attitude was 0.557, indicating that 55.7% of its variance could be explained by AI Literacy and Practical Engagement. For Readiness to Adopt AI, the R^2 value stood at 0.486, reflecting a moderate explanatory power wherein nearly half of the variance is captured by the predictors—Affective Attitude and AI Literacy. Additionally, predictive relevance was evaluated using Stone-Geisser's Q^2 statistic, with both endogenous constructs exhibited predictive relevance, with Q^2 values of 0.341. These values confirm the model's capacity not only to explain but also to predict outcomes with high relevance in the context of AI readiness. *(see Table 6)*

4. Interpretation

The structural model diagram presents the results of a PLS-SEM analysis assessing the influence of AI Literacy, Practical Engagement, and Affective Attitude on Readiness to Adopt AI among students.

The path coefficients (standardized β values) and p-values are displayed on the arrows, confirming statistically significant relationships. Notably, AI literacy significantly predicts affective attitude ($\beta = 0.265$, $p = 0.021$) and has a significant direct effect on AI readiness ($\beta = 0.274$, $p < 0.001$). Its specific indirect effect on readiness through affective attitude is also significant ($\beta = 0.133$, $p = 0.040$), indicating complementary partial mediation. *Practical Engagement* strongly influences *Affective Attitude* ($\beta = 0.567$, $p < 0.001$), which in turn significantly predicts *Readiness* ($\beta = 0.502$, $p < 0.001$). This pathway confirms the mediating function of affect in translating behavioral engagement into readiness.

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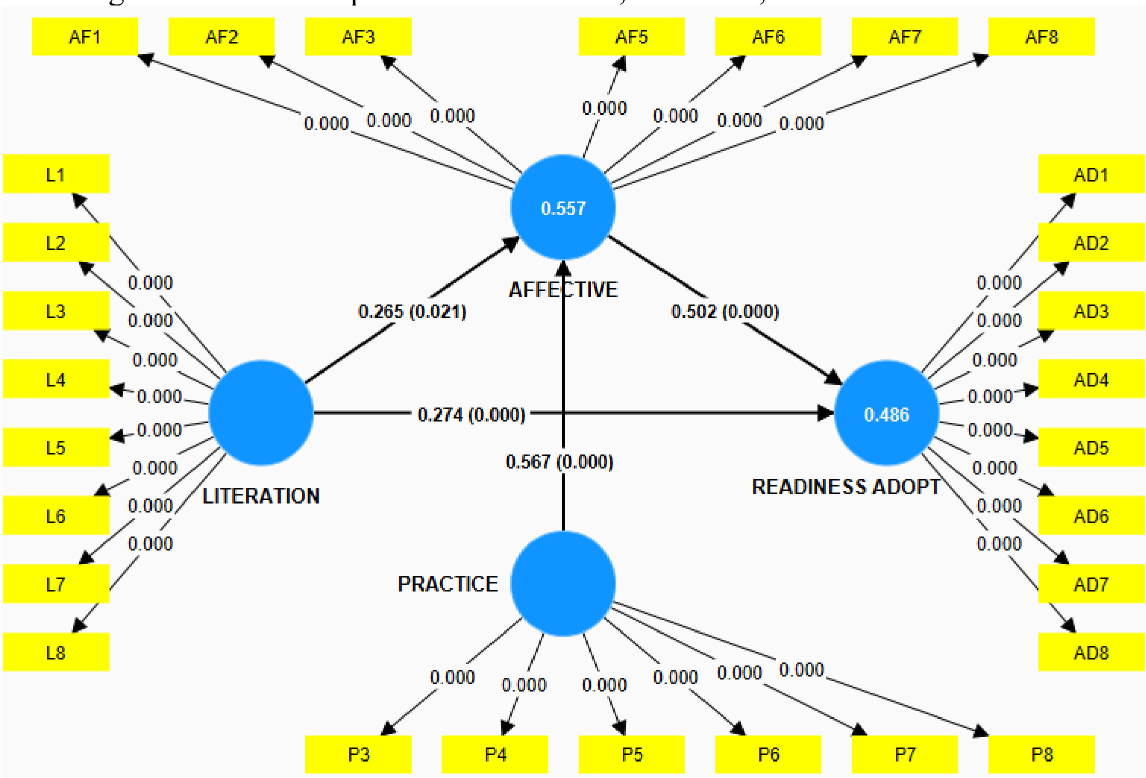
The R^2 values indicate that 55.7% of the variance in *Affective Attitude* and 48.6% in *Readiness to Adopt AI* are explained by the model, suggesting moderate to strong explanatory power. Each observed variable (L1–L8, AF1–AF3, AF4–AF8, P3–P8, AD1–AD8) loads significantly onto its respective latent construct (all $p < 0.001$), confirming convergent validity. *(see Figure 1)*

Figure 1. Relationship between Literation, Affective, Practice and Readiness



Source: Processed Primary Data

5. Hypothesis Testing and Path Coefficients

The hypothesized structural paths were assessed using bootstrapping procedures (5000 subsamples) to determine the significance of the relationships among latent variables. All four hypothesized paths were supported, with standardized path coefficients (β), t-values, and p-values demonstrating statistical significance at the $p < 0.05$ level. *(see Table 7)*

Table 7. Total Effect

Hypothesis	Total Effect Path	β (Original Sample)	t-value	p-value	Decision
H4	Afektif -> Readiness Adopt	0.502	6.191	0.000	Supported
H1	Literation -> Afektif	0.265	2.304	0.021	Supported
H2	Literation -> Readiness Adopt	0.407	5.785	0.000	Supported
H3	Practice -> Afektif	0.567	5.544	0.000	Supported

The strongest relationship was observed between Practical Engagement and Affective Attitude ($\beta = 0.567$, $t = 5.544$, $p < 0.001$), suggesting that experiential interaction with AI tools significantly enhances students' emotional receptiveness toward AI integration. This aligns with experiential learning theory, which posits that direct involvement facilitates affective and cognitive change.

Affective Attitude was also found to be a strong predictor of Readiness to Adopt AI ($\beta = 0.502$, $t = 6.191$, $p < 0.001$). This finding emphasizes the central role of emotional disposition in

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influencing behavioral intention, reinforcing previous studies that highlight affective factors as essential in technology acceptance frameworks.

AI Literacy demonstrated a dual pathway to Readiness to Adopt AI. The direct path was statistically significant (β = 0.274, t = 4.203, $p < 0.001$), indicating that higher levels of conceptual and functional understanding of AI directly enhance readiness. Additionally, AI Literacy exhibited an indirect path through Affective Attitude (β = 0.265, t = 2.304, p = 0.021), confirming a partial mediating effect whereby cognitive competence also contributes to shaping positive affective orientations.

6. Mediation Analysis

Indirect effects were assessed using the bootstrap procedure. Affective attitude significantly mediated both the AI literacy–readiness and practical engagement–readiness relationships. *(see Table 8)*

Table 8. Mediation Variable

Hypothesis	Indirect Path	β (Original Sample)	t-value	p-value	Decision
H5	Literation → Affective → Readiness Adopt	0.133	2.056	0.040	Complementary partial mediation
H6	Practice → Affective → Readiness Adopt	0.285	4.288	0.000	Indirect-only mediation

The indirect effect of AI Literacy on Readiness to Adopt AI via Affective Attitude was statistically significant (β = 0.133, t = 2.056, p = 0.040), indicating a partial mediation. This suggests that while AI literacy exerts a direct influence, its full effect on readiness is realized through the enhancement of students' emotional receptiveness to AI. This mediating mechanism reflects the cognitive-affective-behavioral model, in which knowledge promotes positive emotions, subsequently fostering behavioral intention.

More prominently, Practical Engagement demonstrated a stronger indirect effect on Readiness to Adopt AI through Affective Attitude (β = 0.285, t = 4.288, $p < 0.001$). This complete mediation implies that students' direct experience with AI tools significantly shapes their emotional disposition, which in turn determines their readiness. The absence of a direct modeled path from Practical Engagement to Readiness further reinforces the centrality of affective responses in translating experiential learning into behavioral outcomes.

Discussion

Principal Findings

The study produced three principal findings. First, AI literacy had a significant direct effect on AI readiness and an additional indirect effect through affective attitude. Second, practical engagement strongly predicted affective attitude and contributed to readiness through this pathway. Third, affective attitude was the strongest direct predictor of readiness. These results indicate that AI readiness develops through cognitive capability, practical experience, and a favourable but realistic evaluation of AI. This pattern is consistent with studies showing that readiness, self-efficacy, attitudes, and engagement jointly shape students' AI use (Falebita & Kok, 2025; Li et al., 2024).

The model explained 55.7% of affective attitude and 48.6% of AI readiness. These values indicate meaningful explanatory power while leaving room for institutional, social, and individual factors outside the model. AI literacy supplies an informed basis for use, practical engagement provides experiential evidence, and affective attitude translates both into confidence and willingness to apply AI in business settings.

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AI Literacy and AI Readiness

AI literacy contributed directly to students' readiness to use AI in business. Students who understand AI concepts, applications, risks, and limitations can better evaluate when and how AI should be applied (Laupichler et al., 2022). This finding is consistent with studies linking AI literacy to adoption-related outcomes and academic preparedness (Falebita & Kok, 2025; You et al., 2024). The direct effect confirms an independent cognitive contribution to readiness.

The significant indirect effect through affective attitude indicates that literacy also shapes readiness through evaluation. Greater understanding may reduce ambiguity, support realistic expectations, and help students distinguish useful from inappropriate applications. Within TAM's broader logic, favourable evaluations support acceptance-related outcomes. However, affective attitude remains distinct from perceived usefulness and perceived ease of use. The model extends TAM by showing that domain-specific knowledge influences readiness directly and through affective evaluation (Davis, 1989; Li et al., 2024).

Practical Engagement and Affective Attitude

Practical engagement had the strongest effect on affective attitude ($\beta = 0.567$, $p < 0.001$). This supports experiential learning theory, in which competence and confidence develop through experience, reflection, conceptualization, and experimentation. Students applying AI in assignments, simulations, projects, or business tasks can observe its usefulness and limitations directly. Structured exposure may therefore reduce uncertainty and promote evidence-based evaluations (DeVasto & Palmer, 2024; Ganguli, 2025; Kong et al., 2021; Yalcinkaya et al., 2024).

The absence of a direct modeled path from practical engagement to readiness indicates that experience does not automatically produce preparedness. Practical exposure contributes when it improves optimism, comfort, and confidence. This highlights the importance of guided rather than incidental AI use. Activities should combine application with reflection, feedback, and evaluation of AI-generated outputs so that interaction develops meaningful readiness rather than superficial familiarity.

Mediating Role of Affective Attitude

Affective attitude was the strongest direct predictor of AI readiness ($\beta = 0.502$, $p < 0.001$) and significantly mediated the effects of both AI literacy and practical engagement. The literacy pathway demonstrated complementary partial mediation: knowledge contributed directly to readiness while also supporting favourable attitudes. The engagement pathway demonstrated indirect-only mediation within the specified model, suggesting that practical experience contributes to readiness primarily when it produces positive and realistic evaluations of AI.

These results clarify how capability and exposure become readiness. AI literacy provides an informed basis for evaluation, whereas practical engagement provides experiential evidence. Affective attitude integrates both into confidence and willingness to use AI in business. This interpretation is consistent with evidence that attitudes and self-efficacy are central to AI use (Bati et al., 2024; Falebita & Kok, 2025; Wu & Qin, 2025). Readiness therefore requires optimism accompanied by ethical awareness and realistic appraisal.

Institutional and Pedagogical Recommendations

The findings indicate several connected priorities for universities seeking to strengthen AI readiness among business students:

1. **Curriculum Integration:** Embed AI literacy in relevant business and social-science courses as a strategic competency covering concepts, applications, risks, limitations, ethics, and AI-supported decisions (Obenz & Kileste, 2025).

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2. **Structured Practical Learning:** Provide guided projects, simulations, case analyses, and AI-assisted assignments requiring students to compare outputs, identify errors, justify decisions, and reflect on appropriate use.
3. **Affective Readiness:** Develop confidence, realistic expectations, and comfort in human–AI collaboration through reflective discussion, feedback, and ethical business cases.
4. **Faculty Development:** Support lecturers in AI concepts, instructional design, assessment, academic integrity, and critical evaluation of generated content.
5. **Infrastructure Development:** Provide appropriate tools, secure learning environments, and relevant datasets, accompanied by pedagogical guidance to prevent superficial or mechanical use.
6. **Assessment Diversification:** Evaluate cognitive understanding, practical application, and affective readiness through portfolios, simulations, case-based decisions, and reflective analysis.
7. **Institutional Coordination:** Align curriculum, technology policy, ethical guidance, and industry engagement. Partnerships may supply authentic business problems, but their effectiveness should be evaluated. Together, these measures follow the model's sequence: instruction builds literacy, structured experience shapes attitude, and informed favourable attitudes strengthen readiness (Southworth et al., 2023).

Contribution to Literature

This study contributes to technology-readiness research through a parsimonious model integrating cognitive, experiential, and affective dimensions. Rather than treating readiness as a direct consequence of knowledge or exposure, it identifies affective attitude as a mechanism connecting these antecedents to readiness. The model extends TAM by incorporating AI literacy and practical engagement as domain-specific antecedents while preserving the distinction between attitude, perceived usefulness, and perceived ease of use.

The findings also apply experiential learning theory by showing that direct experience contributes to readiness through affective evaluation. The contribution lies not in adding theories, but in showing how two complementary perspectives explain different parts of readiness. TAM accounts for favourable evaluation, whereas experiential learning explains how structured interaction shapes it. This integration helps explain why students with similar knowledge may differ in readiness when their experience and affective orientation differ.

Limitations and Future Directions

Several limitations qualify the findings. The cross-sectional design does not establish causal or temporal relationships, so mediation represents statistical rather than definitive causal evidence. Voluntary online sampling may introduce self-selection bias, while the Greater Jakarta setting and broad disciplinary composition limit generalization. Self-reported measures may be affected by social desirability and common method variance; the absence of a formal CMV diagnostic remains a limitation. Future studies should use multi-institution probability sampling, longitudinal or experimental designs, objective AI-performance measures, and explicit CMV tests. They should also examine institutional support, field of study, ethical orientation, prior training, and digital access as potential moderators.

CONCLUSION

This study examined how AI literacy, affective attitude, and practical engagement contribute to undergraduate students' readiness to use artificial intelligence in business

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contexts, as well as the extent to which affective attitude mediates the effects of AI literacy and practical engagement on AI readiness.

The first research question is answered by showing that AI readiness is shaped through distinct but interconnected cognitive, affective, and experiential pathways. AI literacy had a significant direct effect on AI readiness, indicating that students' understanding of AI concepts, applications, limitations, risks, and business uses independently strengthens their preparedness to use AI. Affective attitude also had a significant direct effect and emerged as the strongest direct predictor of AI readiness. This result demonstrates that optimism, confidence, perceived relevance, and comfort in working with AI are central components of preparedness. Practical engagement did not contribute to readiness through a direct path in the specified model; instead, it exerted its influence through affective attitude. The model explained 48.6% of the variance in AI readiness, indicating that these three dimensions provide meaningful explanatory power while leaving room for other institutional, social, and individual determinants.

The second research question is answered by the significant mediating role of affective attitude. In the relationship between AI literacy and AI readiness, affective attitude demonstrated complementary partial mediation. This means that AI literacy strengthens readiness both directly and indirectly by helping students develop more informed and favourable evaluations of AI. In the relationship between practical engagement and AI readiness, affective attitude demonstrated indirect-only mediation within the specified model. Thus, practical exposure contributes to readiness primarily when it develops students' confidence, comfort, optimism, and realistic understanding of AI use.

These findings support a parsimonious interpretation of AI readiness. AI literacy provides the cognitive foundation, practical engagement supplies experiential evidence, and affective attitude translates both into willingness and confidence to use AI in future business practice. The study therefore extends the broader logic of the Technology Acceptance Model by incorporating AI literacy and practical engagement as domain-specific antecedents, while experiential learning theory explains how structured interaction with AI shapes affective evaluation.

For business education, the findings indicate that AI readiness cannot be developed through technical instruction alone. Universities should integrate conceptual and ethical AI literacy, structured projects, simulations, case-based assignments, reflective evaluation, and confidence-building activities within a coherent curriculum. Institutional support should also include faculty development, appropriate technological infrastructure, critical assessment of AI-generated outputs, and policies that promote responsible AI use.

The findings should be interpreted in light of the cross-sectional design, voluntary online sampling, self-reported measures, and the limited geographical and disciplinary coverage of the sample. Future research should employ longitudinal, experimental, and multi-institution designs; use probability-based sampling and objective measures of AI competence; formally assess common method variance; and examine additional factors such as institutional support, prior training, digital access, ethical orientation, and field of study.

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