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The Double-Edged Role of AI Literacy in AI Adoption: Trust, Job-Loss Threat, and Career-Stage Differences Among Indonesian Accounting and Finance Professionals

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Abstract

Artificial intelligence (AI) is becoming embedded in accounting and finance work, yet greater knowledge of AI may produce both confidence and concern. This study reanalyzes an open dataset of Indonesian accounting and finance professionals to examine a double-edged model in which AI literacy is associ-ated with trust in AI and perceived job-loss threat, which in turn are linked to intention to adopt AI. Personal innovativeness is included as an additional adoption driver, and birth cohort is used as a proxy for career stage in multi-group analysis. Of 572 archived responses, 550 complete cases were analyzed using reflective composite scores, reliability and discriminant-validity diagnos-tics, standardized path models, and 5,000 bootstrap resamples. AI literacy was positively associated with trust ($\beta = .297$, $p < .001$) and job-loss threat ($\beta = .307$, $p < .001$). Trust ($\beta = .359$, $p < .001$) and personal innovativeness ($\beta = .475$, $p < .001$) were positively associated with adoption intention, whereas job-loss threat and the direct AI-literacy path were not significant in the full sample. Trust significantly mediated the AI-literacy–intention relationship (in-direct effect = .107, 95% CI [.059, .168]), while threat did not. Multi-group re-sults showed significant Gen Z–Millennial differences for AI literacy → threat and threat → intention. The findings suggest that AI literacy can simultaneously increase confidence in AI and awareness of employment risk, but these psychological responses do not translate into adoption in the same way across career stages.

Keywords:
AI literacy; AI adoption; Accounting professionals; Indonesia; Composite-based SEM.

1. INTRODUCTION

Artificial intelligence has moved from a specialist technology to a practical work tool used for information retrieval, document preparation, analytics, forecasting, anomaly detection, and decision support. Accounting and finance are particularly exposed because many professional tasks are data intensive, rules based, and in-creasingly supported by machine learning and generative AI. Recent accounting research shows that AI can improve audit and accounting processes while also changing professional roles, required skills, and the boundaries between human judgment and automated analysis (Fedyk et al., 2022; Han et al., 2023; Stratopoulos & Wang, 2025). Studies of accounting practitioners further indicate that technology adoption depends not only on technical availability but also on staff perceptions, organizational context, and confidence in using new systems (Al Wael et al., 2024; Assidi et al., 2025; Jackson & Allen, 2024; Norzelan et al., 2024).

The Indonesian setting makes these questions timely. Indonesian media reporting on Microsoft and LinkedIn surveys has described extensive workplace use of genera-tive AI, including a reported 92% of Indonesian workers using generative AI at work in 2024 (Setyowati, 2025). The 2025 Microsoft Work Trend Index, as reported local-ly, indicated that 59% of Indonesian business leaders said their organizations were

already using AI agents to automate work processes (Ridwan, 2025; Riyanto & Pertiwi, 2025). At the same time, demand for employees who can understand and operationalize AI is increasing (Pertiwi, 2025), while Indonesia's Ministry of Man-power has framed AI as both a source of task replacement and a reason for continu-ous competence development (ANTARA, 2025). These reports are contextual rather than theoretical evidence, but they illustrate why professional adoption is no longer only a technology question; it is also a workforce and career question.

One construct that can connect these issues is AI literacy: the knowledge and ca-pability needed to understand, evaluate, and use AI appropriately. Research increas-ingly treats AI literacy as more than basic tool familiarity. It includes conceptual understanding, critical evaluation, practical interaction, and awareness of implica-tions and limitations (Celik, 2023; Chiu et al., 2024; Hornberger et al., 2023; Li & Kim, 2024; Pinski & Benlian, 2024; Stolpe & Hallström, 2024). In professional and educational settings, stronger AI literacy can improve readiness, adaptability, and acceptance because users better understand what a system can do and how to work with it (Imjai et al., 2025; Qi et al., 2025). However, greater knowledge can also make the automation potential of AI more visible. Familiarity with AI may therefore create confidence and concern at the same time rather than producing a uniformly positive attitude (Horowitz et al., 2024).

This tension is especially relevant in accounting and finance. Professionals can value AI for speed, consistency, pattern recognition, and decision support while also recognizing that the same capabilities may automate parts of reporting, analysis, compliance, and audit work. Workplace research shows that automation can generate simultaneous optimistic and insecure appraisals (Gödöllei & Beck, 2023), and AI-related job insecurity can affect psychological safety and employee behavior (Kim & Kim, 2024). Other studies show that perceived employability and career behavior can shift when organizations adopt AI (Lin et al., 2024), while trust and human-AI collaboration can support career sustainability (Kong et al., 2023). Thus, an AI-literate professional may be more willing to trust AI and more aware of job dis-placement risk at the same time.

Prior AI-adoption research has established the importance of perceived useful-ness, trust, self-efficacy, and personal characteristics (Kelly et al., 2023; Kaplan et al., 2023; Montag et al., 2023). Yet fewer studies examine trust and employment threat as parallel mechanisms linking AI literacy to adoption, particularly among accounting and finance professionals in an emerging-market setting. Career stage is another underdeveloped dimension. Recent work suggests that AI can have different implications across career stages because experience, occupational identity, time horizon, and perceived replaceability vary across generations and stages of profes-sional development (Bankins et al., 2024; Jeong & Kim, 2025; Seyfi et al., 2025).

This study addresses these gaps through a secondary reanalysis of an open dataset of Indonesian accounting and finance professionals (Setiawan et al., 2026). The study asks three questions: (1) does AI literacy relate simultaneously to trust in AI and perceived job-loss threat; (2) do these mechanisms transmit the association be-tween AI literacy and adoption intention; and (3) do the structural relationships vary across birth-cohort groups used as a proxy for career stage? The contribution is not to argue that threat must reduce adoption. Instead, the study tests whether literacy creates two psychologically different responses and whether their consequences are contingent on career stage. This distinction matters because AI training policies may increase understanding without automatically resolving employment concerns.

2. RESEARCH METHOD

2.1. Research Framework

Figure 1 summarizes the proposed model. AI literacy is modeled as a common antecedent of both trust and job-loss threat, while trust and threat act as parallel mediators. Personal innovativeness provides an additional direct pathway to adoption intention. Career stage is not modeled as a reflective latent construct; instead, group differences are assessed through multi-group comparison.

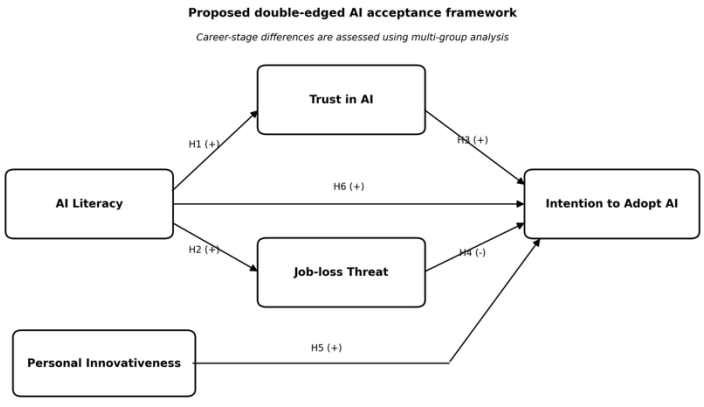


Figure 1. Proposed research framework. Figure caption is placed below the figure

2.2. Data Source and Sample

The study uses a secondary dataset archived in Mendeley Data under the title "Dataset for: The Double-Edged Role of AI Literacy: Career-Stage Differences in AI Acceptance Among Accounting and Finance Professionals" (Setiawan et al., 2026). The repository describes anonymized survey responses from Indonesian accounting and finance professionals and identifies five focal constructs: AI literacy, perceived trust, perceived threat of job loss, personal innovativeness, and intention to adopt AI. The archived CSV contains 572 records and 58 columns, including eligibil-ity/consent fields, profile variables, AI-use questions, and multi-item blocks labeled P1–P11.

Twenty-two records contained missing values across the focal measurement items and were excluded using complete-case analysis, leaving N = 550 for the structural analysis. The complete sample consisted of 232 respondents in the 1997–2007 birth cohort (42.2%), 268 in the 1981–1996 cohort (48.7%), and 50 in the 1946–1980 combined cohort (9.1%). For multi-group analysis, these groups are labeled Gen Z, Millennials, and Gen X+, respectively. Birth cohort is used only as a practical proxy for career stage because the public CSV does not provide a direct career-stage varia-ble with interpretable labels.

Table 1. Complete-case sample distribution by birth cohort

Career-stage proxy	n	%
Gen Z (1997–2007)	232	42.2
Millennials (1981–1996)	268	48.7
Gen X+ (1946–1980)	50	9.1

2.3. Construct Operationalization

A limitation of the public archive is that the CSV contains item codes but not the questionnaire wording or a separate codebook. The repository metadata identifies the five focal constructs, while the observed item blocks provide their anonymized indicators. For this secondary reanalysis, the construct blocks were mapped from the repository description and block structure as follows: AI literacy (P1a–P1b), trust in AI (P8a–P8f), job-loss threat (P10–P10.1), personal innovativeness (P9a–P9c), and intention to adopt AI (P11–P11.2). This mapping is analytically coherent and produces strong internal consistency, but it should be cross-checked against the original questionnaire if the instrument becomes available. The paper therefore treats construct labels as repository-informed secondary mappings rather than claiming access to unarchived item wording.

All focal indicators were coded on a common five-point response scale in the archived data. Construct scores were calculated as equal-weight item means and standardized before structural estimation. This composite procedure is consistent with the prediction-oriented logic commonly used in PLS-SEM applications, while avoiding a false claim that proprietary SmartPLS software was used. Reliability was assessed with Cronbach's alpha and composite reliability (CR), convergent validity with average variance extracted (AVE), and discriminant validity with the heterotrait-monotrait ratio (HTMT).

2.4. Analytical Procedure

The analysis proceeded in four stages. First, descriptive statistics and measurement diagnostics were calculated. Second, standardized path models estimated AI literacy → trust, AI literacy → threat, and the simultaneous effects of AI literacy, trust, threat, and personal innovativeness on adoption intention. Third, 5,000 nonparametric bootstrap resamples were used to obtain standard errors, percentile 95% confidence intervals, and indirect effects. Fourth, the model was re-estimated separately for Gen Z, Millennials, and Gen X+, and bootstrap differences were calculated for pairwise group comparisons. Variance inflation factors (VIF) were used to assess collinearity and f^2 values to describe the incremental contribution of each predictor to adoption intention. Because the data are cross-sectional, all estimated paths are interpreted as associations within the specified model rather than causal effects.

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Measurement Model

Table 2 reports the measurement diagnostics. All Cronbach's alpha values ex-ceeded .84, CR values exceeded .92, and AVE values exceeded .79. Indicator load-ings ranged from .870 to .962 across the five focal constructs. These results indicate strong internal consistency and convergent validity. The high reliability values also warrant attention to construct distinctiveness, so HTMT was examined separately.

Table 2. Measurement model diagnostics

Construct	Loadings	α	CR	AVE	M	SD
AI Literacy	0.929–0.930	0.842	0.927	0.864	3.761	1.039
Trust in AI	0.890–0.920	0.957	0.965	0.823	3.883	0.889
Job-loss Threat	0.961–0.963	0.919	0.961	0.926	3.733	1.059

Personal Innovativeness	0.882–0.910	0.868	0.922	0.797	3.954	0.830
Intention to Adopt AI	0.905–0.927	0.908	0.942	0.844	4.098	0.772

HTMT values were below .90 for all construct pairs. The largest values were per-sonal innovativeness–intention (.862) and trust–personal innovativeness (.859). Thus, discriminant validity is acceptable under the .90 criterion, but these two pairs exceed the more conservative .85 rule. The overlap is substantively plausible be-cause innovative professionals tend to report stronger adoption intention and be-cause trust can coexist with a general openness to technology; nevertheless, the re-sult is treated as a limitation rather than ignored.

Table 3. HTMT discriminant-validity matrix

Construct	AIL	TRU	THR	PI	INT
AIL	—	—	—	—	—
TRU	0.331	—	—	—	—
THR	0.349	0.797	—	—	—
PI	0.432	0.859	0.776	—	—
INT	0.286	0.793	0.673	0.862	—

Note. AIL = AI literacy; TRU = trust in AI; THR = job-loss threat; PI = personal innovativeness; INT = intention to adopt AI.

3.1.2. Structural Model

The structural results are shown in Table 4 and Figure 2. AI literacy was positive-ly associated with trust ($\beta = .297$, $p < .001$) and job-loss threat ($\beta = .307$, $p < .001$), supporting H1 and H2. Trust was positively associated with adoption intention ($\beta = .359$, $p < .001$), supporting H3. Contrary to H4, job-loss threat did not show a signif-icant negative relationship with intention ($\beta = .026$, $p = .575$). Personal innovative-ness was the strongest direct predictor of intention ($\beta = .475$, $p < .001$), supporting H5. The direct effect of AI literacy on intention was small, negative, and nonsignifi-can't ($\beta = -.041$, $p = .195$), so H6 was not supported.

The model explained 8.8% of the variance in trust, 9.4% in job-loss threat, and 63.2% in intention to adopt AI. VIF values for the intention equation ranged from 1.17 to 3.25, below the common threshold of 5. Incremental effect sizes were negli-gible for AI literacy and threat, approximately .108 for trust, and .210 for personal innovativeness. The pattern indicates that literacy matters primarily through how it shapes users' interpretation of AI rather than through a strong direct path to adoption.

Table 4. Structural path estimates and hypothesis tests

Path	β	SE	95% CI	p	f^2/VIF	Decision
H1: AIL -> TRU	0.297	0.051	[0.197, 0.399]	<.001	—	Supported
H2: AIL -> THR	0.307	0.049	[0.214, 0.407]	<.001	—	Supported
H3: TRU -> INT	0.359	0.062	[0.242, 0.487]	<.001	0.108/3.25	Supported
H4: THR -> INT	0.026	0.051	[-0.073, 0.129]	0.575	0.001/2.46	Not supported
H5: PI -> INT	0.475	0.071	[0.331, 0.608]	<.001	0.210/2.93	Supported
H6: AIL -> INT	-0.041	0.032	[-0.102, 0.022]	0.195	0.004/1.17	Not supported

Note. f^2/VIF is reported only for predictors in the intention equation; endogenous mediator equations contain one predictor. Bootstrap resamples = 5,000.

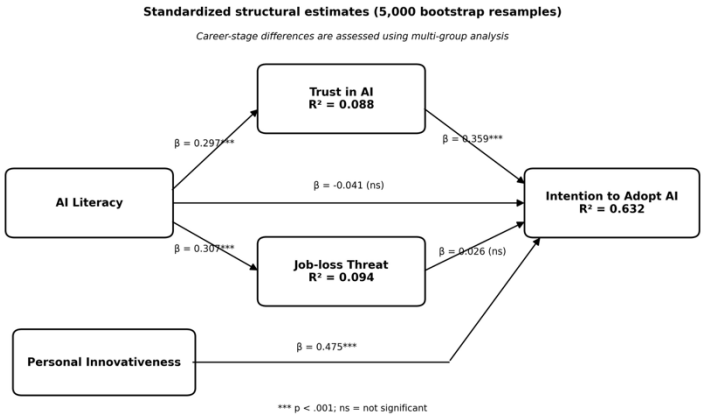


Figure 2. Standardized structural results. Figure caption is placed below the figure

3.1.3. Mediation Effects

The mediation results sharpen the double-edged interpretation. The indirect effect through trust was positive and significant (indirect = .107, 95% CI [.059, .168], p < .001), supporting H7. The indirect effect through job-loss threat was small and non-significant (indirect = .008, 95% CI [−.023, .040], p = .575), so H8 was not support-ed. This means that AI literacy was associated with both trust and threat, but only the trust pathway transmitted a reliable association to adoption intention in the full sample.

Table 5. Bootstrap mediation results

Hyp.	Indirect path	Effect	SE	95% CI	Decision
H7	AIL -> TRU -> INT	0.107	0.027	[0.059, 0.168]	Supported
H8	AIL -> THR -> INT	0.008	0.016	[-0.023, 0.040]	Not supported

3.1.4. Career-Stage Multi-Group Analysis

Group-specific coefficients showed that the AI literacy → threat path was strongest for Gen Z (β = .427), smaller for Millennials (β = .187), and intermediate for Gen X+ (β = .277). The threat → intention coefficient was positive for Gen Z (β = .204) but slightly negative for Millennials (β = −.064) and Gen X+ (β = −.042). Pairwise bootstrap comparison confirmed two significant Gen Z–Millennial differences: AI literacy → threat (Δβ = .240, p = .013) and threat → intention (Δβ = .268, p = .009). No other pairwise path differences reached p < .05, and comparisons involving Gen X+ should be interpreted cautiously because that group contains only 50 observations. H9 is therefore partially supported.

Table 6. Career-stage multi-group path comparison

Path	Gen Z	Mill.	Gen X+	Δ Z–M	p Z–M	Inference
AIL→TRU	0.384	0.231	0.097	0.153	0.130	No diff.
AIL→THR	0.427	0.187	0.277	0.240	0.013	Different
AIL→INT	-0.043	-0.034	-0.045	-0.009	0.869	No diff.
TRU→INT	0.339	0.362	0.227	-0.023	0.852	No diff.
THR→INT	0.204	-0.064	-0.042	0.268	0.009	Different
PI→INT	0.370	0.515	0.666	-0.144	0.306	No diff.

Note. Δ Z–M = Gen Z coefficient minus Millennial coefficient. Gen Z n = 232; Millennials n = 268; Gen X+ n = 50. Only the Gen Z–Millennial comparison is shown in detail because it contained the statistically significant differences.

3.2. Discussion

3.2.1. AI Literacy Produces Two Responses, but Only One General Adoption Mechanism

The central finding is that AI literacy is genuinely double-edged at the appraisal stage. More literate professionals reported both greater trust and greater perceived job-loss threat. This pattern fits the idea that familiarity with AI can reduce uncertainty while simultaneously revealing its disruptive capacity (Horowitz et al., 2024). It also aligns with automation research showing that optimism and insecurity are not mutually exclusive reactions (Gödöllei & Beck, 2023). For accounting and finance professionals, understanding how AI can automate reconciliation, reporting, anomaly detection, document review, forecasting, and routine analysis can make technology appear both more useful and more capable of changing the occupational task bundle.

However, the two edges are not symmetrical in their behavioral consequences. Trust strongly predicted intention and carried a significant indirect effect from literacy to intention. Job-loss threat did not predict intention in the full sample and did not mediate the literacy relationship. This result is consistent with accounting-education evidence showing that perceived threat can be psychologically meaningful without necessarily reducing technology-use intention (Kuang, Karnalim, & Setiawan, 2026). It also supports broader trust research that treats calibrated trust as a proximal mechanism of actual willingness to rely on AI (Bach et al., 2024; Daly et al., 2025; Kaplan et al., 2023).

The nonsignificant direct literacy path is also theoretically informative. AI literacy appears to be an upstream capability rather than a sufficient adoption motive. Knowing more about AI does not automatically create a plan to use it. Literacy becomes behaviorally meaningful when it changes beliefs about reliability, value, and compatibility with professional work. This interpretation is consistent with research showing that AI acceptance is shaped by combinations of competence, trust, usefulness, and individual dispositions rather than knowledge alone (Kelly et al., 2023; Montag et al., 2023; Norzelan et al., 2024).

3.2.2. Personal Innovativeness Is the Strongest Proximal Driver

Personal innovativeness had the largest direct coefficient in the intention equation. This finding suggests that organizations should not assume that literacy programs alone will produce adoption. Some employees are naturally more willing to experiment, tolerate early-stage imperfections, and explore new workflows. Generative-AI studies similarly identify personal innovativeness as an important behavioral driver (Wu et al., 2025), while technology-adoption research in accounting highlights staff confidence, ease of use, and organizational support as practical enablers (Jackson & Allen, 2024). The implication is that adoption programs

should combine literacy with opportunities for low-risk experimentation, peer demonstration, and role-relevant use cases.

The result also helps explain why personal innovativeness and intention showed relatively high HTMT. The constructs are not identical, but in an emerging technology context, a general disposition to try new technology naturally overlaps with specific intention to use AI. Future studies should separate trait innovativeness from domain-specific AI innovativeness and should validate construct wording directly rather than relying on coded secondary blocks.

3.2.3. Career Stage Changes the Meaning of Threat

The multi-group results provide the most distinctive extension of the full-sample model. AI literacy was more strongly associated with job-loss threats among Gen Z than among Millennials, and threat was more positively associated with intention among Gen Z. This does not mean job-loss threat is beneficial. A more careful interpretation is that younger professionals may respond to perceived risk through adaptive or defensive adoption: when AI threatens entry-level or routine tasks, learning and using AI may be perceived as a strategy for remaining competitive. This interpretation is consistent with career research showing that the same technological disruption can activate different career behaviors depending on future orientation and perceived employability (Bankins et al., 2024; Lin et al., 2024).

For Millennials, the threat–intention path was slightly negative and nonsignificant. Mid-career professionals may have more accumulated task knowledge, organizational relationships, and role-specific capital, which can reduce the need to respond to threat through immediate adoption. The Gen X+ estimate should not be overinterpreted because the group is small. Nevertheless, the pattern reinforces findings from other domains that trust and resistance toward AI vary by generation (Jeong & Kim, 2025; Seyfi et al., 2025). Career-stage differences therefore deserve direct measurement in future accounting research rather than being treated as demographic control only.

3.2.4. Implications for Accounting and Finance Organizations

For firms, the results imply that AI capability programs should be designed around both competence and psychological interpretation. First, training should teach not only how to prompt or operate tools but also how to evaluate outputs, detect failure modes, document human oversight, and identify which tasks require professional judgment. Such calibrated literacy is more likely to create warranted trust rather than blind reliance. Second, organizations should communicate how AI changes task portfolios and career pathways. Job-loss concerns cannot be solved by adoption campaigns that emphasize efficiency while ignoring employment consequences. AI-resistance research suggests that accessibility, augmentation narratives, legitimacy, and organizational support are important for reducing fear and mistrust (Golgeci et al., 2025).

Third, accounting and finance leaders should create role-specific pathways. Early career staff may need explicit assurance that AI proficiency is connected to progression into analysis, judgment, client communication, and control functions rather than only faster execution of routine work. Mid-career professionals may need reskilling that integrates AI with domain expertise and managerial responsibility. For senior professionals, governance, accountability, model risk, and oversight may be more relevant than tool-level training. This differentiated approach is consistent with recent finance-professional evidence that familiarity and knowledge shape attitudes toward AI adoption (Hu et al., 2026) and with accounting scholarship emphasizing the profession's movement toward higher-value analytical and judgment tasks (Assidi et al., 2025; Stratopoulos & Wang, 2025; Tharapos et al., 2025).

These implications are also consistent with Indonesia's current labor-market discourse. Local reporting emphasizes both rising demand for AI-related skills and the need for workers to update competencies as some tasks are automated (ANTARA, 2025; Pertiwi, 2025). The empirical results suggest that organizations should treat that tension directly: literacy can make employees more confident in AI, but it can also make employment risk more visible. The managerial objective should be to convert awareness into credible augmentation pathways rather than suppressing concern.

4. CONCLUSION

This study reanalyzed an open dataset of Indonesian accounting and finance pro-fessionals to examine whether AI literacy has a double-edged role in AI acceptance. The results support the double-edged idea at the appraisal stage: AI literacy was positively associated with both trust in AI and perceived job-loss threat. Yet only trust acted as a general pathway to adoption intention. Personal innovativeness was the strongest proximal predictor, while neither job-loss threat nor the direct AI-literacy path was significant in the full sample. Career-stage analysis added im-portant nuance because younger professionals showed a stronger literacy–threat relationship and a more positive threat–intention relationship than Millennials.

The theoretical contribution is therefore more precise than a simple claim that AI literacy has positive and negative effects. Literacy appears to broaden awareness in two directions, but the behavioral consequence of each appraisal depends on what the appraisal represents and for whom. Trust is an enabling mechanism across

the sample, while employment threat is a contingent career response. For practice, AI programs should combine literacy, calibrated trust, experimentation opportunities, and transparent career-development pathways. However, this study still has limitations regarding the dataset, such as a lack of information on the wording of the questionnaire questions, which should be taken into account in future research.

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