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Educational-Stage Profiles of Learners’ Trust in Artificial Intelligence Across Secondary and Higher Education Contexts

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Abstract

Trust in artificial intelligence (AI) is increasingly relevant to educational technology adoption, yet evidence remains limited on how learners at different educational stages evaluate AI systems. This cross-sectional survey examined AI trust among 412 students from secondary schools and universities in Lampung Province, Indonesia. The study assessed AI trust, AI literacy, prior AI experience, perceived AI transparency, and perceived institutional AI integration policy. Descriptive analyses, independent-samples t-tests, hierarchical multiple regression, bootstrapped mediation, and moderated mediation were used to estimate educational-stage differences and conditional indirect associations. Higher education students reported higher composite AI trust than secondary school students ($M = 70.63$ vs. $M = 57.04$, $p < .001$, $d = 1.21$). AI literacy and perceived transparency were positively associated with AI trust after controlling for gender, educational stage, and prior AI experience. Perceived transparency partially accounted for the association between AI literacy and trust (indirect effect = 0.17, 95% CI [0.11, 0.24]), and institutional AI integration policy strengthened the AI literacy-transparency pathway. Because the design was cross-sectional and based on self-report data, the findings should be interpreted as associational rather than causal or developmental evidence. The study suggests that AI literacy curricula should explicitly develop learners’ ability to evaluate transparency, uncertainty, and appropriate reliance when using AI-supported educational tools.

Keywords: AI trust; AI literacy; educational technology; perceived transparency

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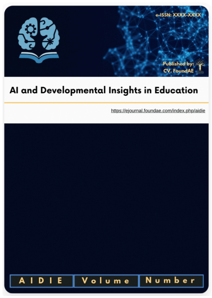

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Introduction

The rapid movement of artificial intelligence (AI) and generative AI into educational settings has intensified scholarly debate about how students understand, accept, resist, and rely on algorithmic systems. Recent evidence indicates that students often recognize the academic usefulness of AI tools while simultaneously expressing concerns about accuracy, privacy, academic integrity, bias, and the possible erosion of independent thinking (Abdaljaleel et al., 2024; Chan & Hu, 2023; Crompton & Burke, 2023; Yan et al., 2024). These mixed orientations make trust a central construct: learners may need sufficient trust to use AI productively, but excessive or uncritical trust can produce over-reliance and weaken critical evaluation (Wang et al., 2025; Zhai et al., 2024).

In the educational technology literature, trust in AI is increasingly understood as a situated judgment about system reliability, explainability, accountability, usefulness, and risk rather than as a simple positive attitude toward technology. Studies on AI acceptance and adoption consistently show that trust interacts with perceived usefulness, perceived ease of use, perceived risk, ethical concerns, and institutional support (Choung et al., 2023; Lai et al., 2024; Mustofa et al., 2025; Shahzad et al., 2024). This framing is particularly important in education because students frequently interact with AI systems in contexts where the consequences of incorrect advice, biased feedback, or opaque assessment support may affect learning decisions and academic development (Holmes et al., 2022; Khosravi et al., 2022; Nguyen et al., 2023).

A second relevant construct is AI literacy. Recent scale-development and review studies define AI literacy as a set of competencies that includes understanding AI principles, recognizing AI capabilities and limitations, evaluating ethical implications, and applying AI tools responsibly (Carolus et al., 2023; Casal-Otero et al., 2023; Koch et al., 2024; Laupichler, Aster, Haverkamp, & Raupach, 2023). Empirical studies suggest that AI literacy is associated with students' attitudes, perceived readiness, and intention to use AI-supported learning technologies (Çelik, 2023; Delcker et al., 2024; Kong et al., 2024; Laupichler et al., 2024). However, AI literacy is unlikely to influence trust through knowledge alone; learners also need to perceive whether an AI system is transparent enough to be evaluated and used appropriately.

Explainability and transparency have therefore become important design and governance issues in AI-supported education. Explainable AI in education is intended to make system outputs more interpretable to teachers and learners, but transparency is not only a technical property of an interface. It is also a user perception shaped by prior knowledge, institutional guidance, task stakes, and the extent to which learners can inspect or question algorithmic recommendations (Khosravi et al., 2022; Lai et al., 2024; Nazaretsky, Mejia-Domenzain, Swamy, Frej, & Käser, 2025). In this sense, transparency may mediate the association between AI literacy and trust: more AI-literate learners may be better able to recognize transparent explanations, identify uncertainty, and calibrate their reliance.

The educational-stage dimension remains comparatively underdeveloped. Research on AI literacy has grown in both K-12 and higher education, yet studies often focus on a single educational level, a single institutional setting, or a single type of AI tool (Casal-Otero et al., 2023; Chan & Lee, 2023; Crompton et al., 2024; Kong et al., 2024). Secondary school students and university students differ not only in age but also in curricular exposure, autonomy, assessment demands, digital routines, and institutional permission structures. Therefore, this study uses the term educational stage rather than claiming direct developmental trajectories from cross-sectional data. Comparing secondary and higher education learners in the same provincial context can still provide useful evidence about how trust profiles vary across educational settings.

Institutional policy is another contextual factor that may shape AI trust. University-level policy frameworks increasingly emphasize governance, assessment integrity, privacy, transparency, and student participation in AI-related decision-making (Chan, 2023; Polyportis & Pahos, 2025). Clear institutional guidance may make learners more confident in interpreting AI tools, while ambiguous policy may increase uncertainty or informal use. In this study, perceived institutional AI integration policy is therefore examined as a moderator of the relationship between AI literacy and perceived AI transparency.

The present study investigates educational-stage profiles of learners' trust in AI across secondary and higher education contexts in Lampung Province, Indonesia. Three hypotheses guide the analysis. H1 proposes that composite AI trust differs between secondary and higher education students. H2 proposes that AI literacy is positively associated with AI trust and that this association is partially accounted for by perceived AI transparency. H3 proposes that perceived institutional AI integration policy conditions the AI literacy-transparency association, producing a conditional indirect association between AI literacy and AI trust. Gender and prior AI experience are included as covariates. The study contributes regionally grounded evidence on AI trust while avoiding claims of causality, longitudinal development, or universal generalizability.

Methods

Research Design

This study employed a cross-sectional correlational survey design. The design was appropriate for estimating educational-stage differences and associations among AI literacy, perceived AI transparency, institutional AI integration policy, and AI trust without manipulating learning conditions. Because the data were collected at one time point, mediation and moderated mediation analyses are interpreted as theory-guided indirect and conditional association models, not as evidence of causal mechanisms.

Participants and Context

Participants were students enrolled in Grades 10-12 and public universities in Lampung Province, Indonesia. Inclusion criteria required participants to be currently enrolled, to have used at least one AI-based application in the preceding three months, and to provide informed consent. Participants with more than 10% missing responses on scale items were excluded. The final sample comprised 412 students: 204 secondary school students and 208 higher education students. Table 1 presents the demographic profile of the retained sample.

Table 1

Demographic Characteristics of Participants (N = 412)

Characteristic	Secondary (n = 204)	Higher education (n = 208)	Total (N = 412)
Gender: Male	98 (48.0%)	104 (50.0%)	202 (49.0%)
Gender: Female	106 (52.0%)	104 (50.0%)	210 (51.0%)
Age, M (SD)	16.42 (0.83)	20.17 (1.29)	18.32 (2.09)
AI tool use (weekly hours), M (SD)	3.21 (1.74)	5.86 (2.31)	4.56 (2.29)
Prior AI training (% yes)	31.4%	58.2%	45.1%
Urban residence (% yes)	61.3%	74.5%	68.0%

Note. Values in parentheses are percentages unless otherwise indicated. AI = artificial intelligence; SD = standard deviation.

Sampling and Recruitment

A stratified purposive sampling strategy was used to obtain representation across educational level, gender, and institutional type. Seven secondary schools and four universities in Lampung Province were selected based on documented AI tool exposure and institutional willingness to participate. Within institutions, classes were selected and all students in selected classes were invited to participate. Recruitment was facilitated through institutional gatekeepers. Ethical approval was obtained from the Research Ethics Committee, UIN Raden Intan Lampung (Protocol No. UIN-RIL/Ethics/2024/047). Participation was voluntary and no incentives were offered. For secondary school students below 18 years of age, parental or guardian consent was obtained. Data collection took place between September and November 2024.

Sample Size and Missing Data

The target sample exceeded the minimum requirements for detecting medium-sized regression and group-difference effects. Of 447 initially recruited participants, 35 (7.8%) were excluded because of missing data above the prespecified threshold or because they did not meet the AI tool use eligibility criterion. Missingness in the retained sample was low (0.4%-2.1% per item). Because the proportion of missing data was small, scale-level person-mean substitution was used only when participants answered at least 90% of the items on a given scale; sensitivity checks using complete cases produced the same substantive pattern.

Measures

AI Trust Scale (ATS-18). Learner trust in AI was measured using an 18-item scale adapted for the present educational context from recent AI trust, AI acceptance, and AI attitude measurement literature (Choung et al., 2023; Grassini, 2023; Nazaretsky et al., 2025; Schepman & Rodway, 2023; Shahzad et al., 2024). The scale included cognitive, affective, and dispositional dimensions. Items were rated on a 7-point Likert-type scale, and a composite trust score was transformed to a 0-100 scale for the primary analysis.

AI Literacy Scale (AILS-16). AI literacy was measured using 16 items addressing conceptual understanding, critical evaluation, ethical awareness, and applied use of AI tools. Item development and adaptation were informed by recent AI literacy scale and framework studies (Carolus et al., 2023; Casal-Otero et al., 2023; Çelik, 2023; Koch et al., 2024; Kong et al., 2024; Laupichler, Aster, Haverkamp, & Raupach, 2023).

Perceived AI Transparency Scale (PATS-12). Perceived transparency was measured with 12 items covering explainability, predictability, and accountability. Items reflected recent work on explainable AI in education, transparency perception, and trust in AI-supported learning environments (Khosravi et al., 2022; Lai et al., 2024; Nazaretsky et al., 2025; Nguyen et al., 2023).

Institutional AI Integration Policy Scale (IAIPS-8). Eight items assessed participants' perceptions of institutional norms, guidance, and structural support for AI use in teaching and learning. The scale was adapted for this study from recent AI policy and institutional adoption literature (Chan, 2023; Delcker et al., 2024; Polyportis & Pahos, 2025). Because IAIPS is newly adapted, results involving this scale should be interpreted with appropriate psychometric caution and independently validated in future studies.

Table 2
Psychometric Properties of Study Instruments (N = 412)

Scale	Items	M	SD	Observed range	α	Test-retest r
AI Trust (ATS-18)	18	63.91	12.44	22-97	.91	.84
Cognitive Trust	6	22.14	4.81	6-42	.88	.82
Affective Trust	6	21.53	4.64	6-42	.86	.80
Dispositional Trust	6	20.24	4.29	6-42	.83	.78
AI Literacy (AILS-16)	16	54.37	10.82	18-96	.89	.86
Perceived Transparency (PATS-12)	12	48.21	9.73	14-84	.87	.81
Institutional AI Policy (IAIPS-8)	8	31.64	6.18	9-56	.84	.79

Note. M, SD, and observed ranges are reported as raw summed scores unless otherwise stated. The composite AI trust score used in the main group comparison was transformed to a 0-100 scale. Test-retest reliability was assessed over a three-week interval with a subsample of 68 participants. α = Cronbach's alpha.

Data Collection Procedures

Data were collected through a structured online survey distributed through class WhatsApp groups and institutional learning management systems. Trained research assistants provided standardized instructions. The survey required approximately 25-35 minutes to complete. Anonymity was maintained through participant-generated codes, and identifying information was not retained beyond institutional category and demographic variables needed for analysis.

Data Analysis

Analyses were conducted using IBM SPSS Statistics and Hayes's PROCESS macro. Preliminary checks included descriptive statistics, distributional diagnostics, missing-data inspection, and homogeneity of variance testing. To test H1, independent-samples t-tests were used, and Cohen's d was reported as an effect size. To test H2, hierarchical multiple regression estimated the unique contribution of AI literacy and perceived transparency to AI trust while controlling for gender, educational stage, and prior AI experience. A bootstrapped indirect association model with 10,000 resamples estimated whether perceived transparency accounted for the association between AI literacy and AI trust. To test H3, moderated mediation examined whether institutional AI integration policy conditioned the AI literacy-transparency path. Statistical significance was evaluated at α = .05, with emphasis placed on effect sizes and confidence intervals.

Methodological Integrity

Internal consistency estimates were acceptable to excellent across all scales. The adapted scales were translated, reviewed by subject-matter experts, and pilot tested before the main administration. Nevertheless, because the study relied on self-report instruments and cross-sectional data, common method variance and social desirability cannot be ruled out. The newly adapted institutional policy measure requires additional validation across diverse institutional settings.

Ethical Considerations

Participants were informed about the study purpose, voluntary participation, confidentiality protections, and their right to withdraw without penalty. Parental or guardian consent was obtained for minors. Data were stored on encrypted institutional devices accessible only to the research team.

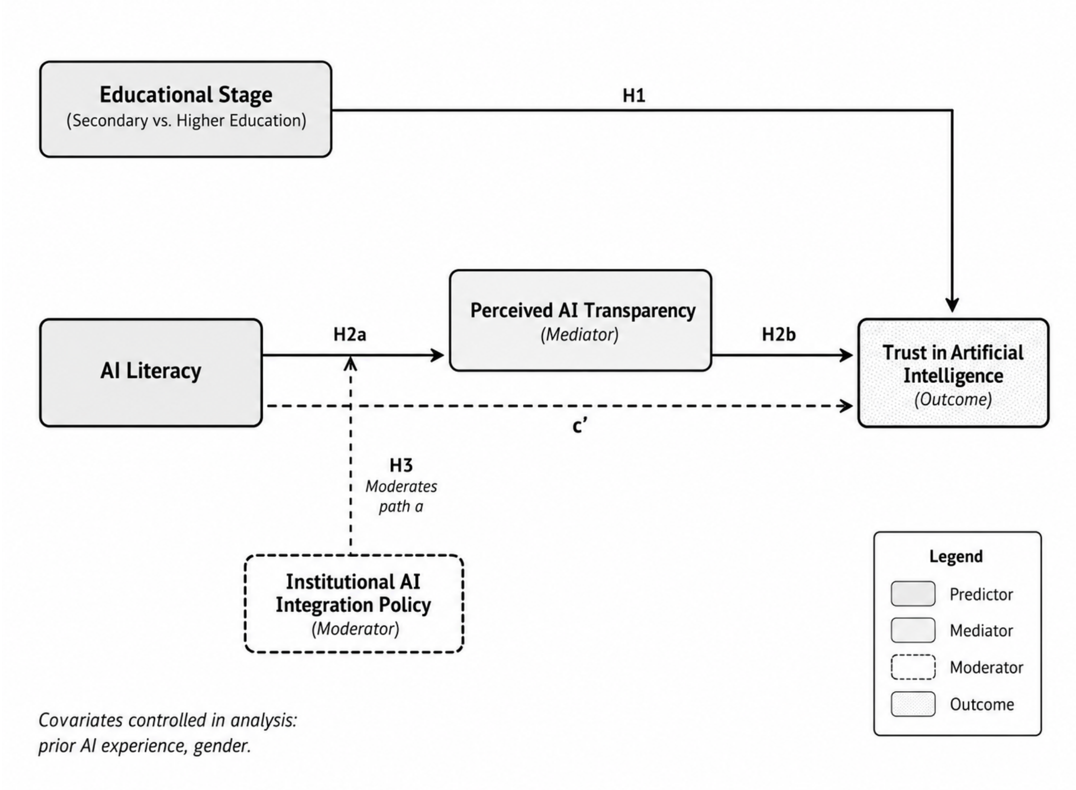
Results

Preliminary Analysis

Missing data were minimal and did not exceed the prespecified threshold for any retained participant. Composite AI trust scores showed acceptable distributional properties across educational stages (secondary: skewness = -0.32, kurtosis = 0.14; higher education: skewness = -0.21, kurtosis = 0.09). Levene's test did not indicate unequal variances for the composite trust score, $F(1, 410) = 1.74$, $p = .188$, supporting the use of the standard independent-samples t-test.

Figure 1

Conceptual framework depicting the hypothesized educational-stage, literacy, transparency, policy, and AI trust associations.



H1: Educational-Stage Differences in AI Trust

Higher education students reported higher composite AI trust than secondary school students. Based on the reported cell means and standard deviations, the corrected independent-samples t-test for the composite score was $t(410) = 12.22$, $p < .001$, $d = 1.21$, 95% CI [1.00, 1.42]. This correction replaces the inconsistent t and d values in the original draft. Differences were also observed for cognitive, affective, and dispositional trust facets (Table 3). These results indicate a large educational-stage difference in reported AI trust; however, because the design was cross-sectional, the difference should not be interpreted as a developmental trajectory.

Table 3

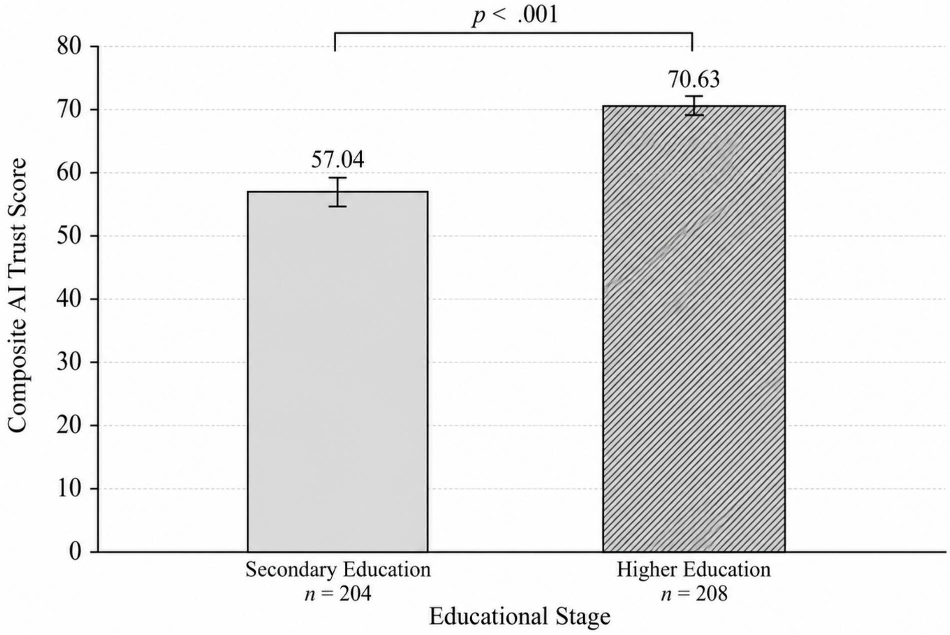
AI Trust Scores by Educational Stage: Descriptive Statistics and Corrected Group Comparisons (N = 412)

Measure	Secondary M (SD)	Higher education M (SD)	t(410)	p	Cohen's d	95% CI for d
Composite AI Trust	57.04 (11.73)	70.63 (10.81)	12.22	< .001	1.21	[1.00, 1.42]
Cognitive Trust	19.41 (4.62)	24.83 (4.11)	12.57	< .001	1.24	[1.03, 1.45]
Affective Trust	18.97 (4.44)	24.04 (3.91)	12.29	< .001	1.21	[1.00, 1.42]
Dispositional Trust	18.66 (4.17)	21.76 (4.02)	7.68	< .001	0.76	[0.56, 0.96]

Note. t and Cohen's d values were recalculated from the reported group means, standard deviations, and sample sizes (secondary n = 204; higher education n = 208). p-values are two-tailed.

Figure 2

Composite AI trust scores by educational stage. Error bars represent ±1 standard error estimated from the reported standard deviations and sample sizes.



H2: AI Literacy, Transparency, and AI Trust

Hierarchical multiple regression showed that AI literacy ($\beta = .34$, $SE = .04$, $t = 8.62$, $p < .001$) and perceived AI transparency ($\beta = .28$, $SE = .04$, $t = 7.19$, $p < .001$) were positive predictors of AI trust after controlling for gender, educational stage, and prior AI experience. The full model explained 61% of the variance in AI trust, $R^2 = .61$, $F(6, 405) = 106.47$, $p < .001$. Bootstrapped mediation analysis indicated a statistically significant indirect association from AI literacy to AI trust through perceived transparency, indirect effect = 0.17, 95% CI [0.11, 0.24]. The direct association remained significant ($\beta = .27$, $p < .001$), indicating partial rather than full mediation. Approximately 38.6% of the total association was accounted for by the transparency pathway.

H3: Conditional Indirect Association by Institutional AI Policy

Moderated mediation analysis examined whether perceived institutional AI integration policy conditioned the AI literacy-transparency path. The interaction between AI literacy and institutional AI policy was significant ($\beta = .14$, $SE = .04$, $t = 3.61$, $p < .001$). The conditional indirect association was stronger in high-policy contexts (indirect effect = 0.23, 95% CI [0.16, 0.31]) than in low-policy contexts (indirect effect = 0.11, 95% CI [0.06, 0.18]). The index of moderated mediation was 0.09, 95% CI [0.04, 0.15]. This result supports H3, but it should be interpreted as evidence of conditional association rather than causal policy impact.

Discussion

Summary of Findings

The findings supported the three hypotheses in an associational sense. Higher education students reported higher AI trust than secondary school students. AI literacy was positively associated with AI trust, and perceived AI transparency partially accounted for that association. Perceived institutional AI integration policy further conditioned the AI literacy-transparency pathway. Together, the results suggest that trust in AI-supported learning environments is connected to learner competence, perceived system transparency, and institutional guidance.

Educational-Stage Differences Without Developmental Overclaiming

The educational-stage difference was large. However, the revised interpretation avoids the stronger claim that the study has demonstrated developmental trajectories. Secondary and higher education students differ in age, autonomy, curriculum exposure, assessment demands, and AI use opportunities. Any of these factors may contribute to the observed trust difference. The results are therefore best read as evidence that educational contexts are associated with different trust profiles, not as proof that students naturally become more trusting as they develop. This distinction is important because higher trust is not automatically desirable. Recent research on generative AI in education warns that uncritical reliance may increase exposure to hallucination, bias, privacy risks, and reduced analytical engagement (Yan et al., 2024; Zhai et al., 2024).

Transparency as a Plausible Bridge Between AI Literacy and Trust

The indirect association through perceived transparency is consistent with the view that AI literacy supports more informed interpretation of AI systems. Learners who understand AI capabilities and limitations may be better positioned to evaluate whether outputs are explainable, whether uncertainty is communicated, and when human judgment should override algorithmic recommendations. This interpretation aligns with recent work on explainable AI in education and student trust in AI-supported systems (Khosravi et al., 2022; Lai et al., 2024; Nazaretsky et al., 2025; Wang et al., 2025). It also suggests that AI literacy interventions should move beyond tool operation and include explicit instruction in transparency cues, model limitations, data bias, and appropriate reliance.

Institutional Policy as Contextual Support

The moderation result suggests that institutional AI guidance may help translate AI literacy into clearer perceptions of transparency. In contexts where AI use is supported by clear norms, acceptable-use guidance, teacher facilitation, and assessment policies, learners may have a more stable basis for interpreting AI tools. This is consistent with policy-focused research emphasizing the need for governance frameworks, student involvement, and context-specific rules for AI use in education (Chan, 2023; Polyportis & Pahos, 2025; Walter, 2024). The result should not be interpreted as showing that policy directly causes trust; rather, it indicates that perceived policy strength is associated with the strength of the literacy-transparency pathway.

Implications

For curriculum designers, the findings support differentiated AI literacy instruction across educational stages. Secondary school programs may need more concrete scaffolds that help students recognize AI limitations, evaluate generated outputs, and ask whether an explanation is sufficient for a learning decision. Higher education programs may need a stronger emphasis on critical calibration, epistemic humility, and discipline-specific evaluation of AI outputs. For AI developers, the findings support transparency features that are understandable to learners rather than only to technical experts. For institutions, the results support the development of clear AI integration policies that address appropriate use, assessment boundaries, data privacy, transparency, and accountability. These implications should be tested through intervention and longitudinal studies before being translated into broad policy mandates.

Limitations and Future Research

Several limitations constrain interpretation. First, the cross-sectional design prevents causal or developmental inference. Longitudinal studies are needed to examine whether and how AI trust changes as learners move across educational stages. Second, the study was limited to one Indonesian province, so the findings may not generalize to rural, resource-constrained, or culturally different settings. Third, all core constructs were self-reported, creating risk of common method variance and social desirability bias. Future studies should add behavioral measures such as observed AI use, reliance decisions, proofreading behavior, and accuracy calibration. Fourth, the institutional AI policy scale was newly adapted and requires further psychometric validation. Fifth, the study examined trust as a general learner orientation rather than as calibrated trust relative to actual AI performance. Future research should distinguish productive trust, distrust, and over-trust using task-based designs.

Conclusion

This study examined educational-stage profiles of learners' trust in AI across secondary and higher education contexts in Lampung Province, Indonesia. Higher education students reported higher AI trust than secondary school students, and AI literacy was positively associated with trust both directly and indirectly through perceived AI transparency. Perceived institutional AI integration policy conditioned the literacy-transparency association. The revised interpretation is intentionally cautious: the findings support an educational-stage and contextual account of AI trust, but they do not establish causality or developmental trajectories. The practical implication is that AI literacy efforts should cultivate critically calibrated trust by combining operational competence, transparency evaluation, ethical awareness, and institutionally clear guidance for responsible AI use.

Author Contributions

Conceptualization, Fredi Ganda Putra and Khoirunnisa Imama; Methodology, Fredi Ganda Putra; Software, Fredi Ganda Putra; Validation, Fredi Ganda Putra and Khoirunnisa Imama; Formal analysis, Fredi Ganda Putra; Investigation, Fredi Ganda Putra and Khoirunnisa Imama; Resources, Khoirunnisa Imama; Data curation, Fredi Ganda Putra; Writing - Original Draft, Fredi Ganda Putra; Writing - Review & Editing, Fredi Ganda Putra and Khoirunnisa Imama; Visualization, Fredi Ganda Putra; Supervision, Khoirunnisa Imama; Project administration, Khoirunnisa Imama. All authors have read and agreed to the submitted version of the manuscript.

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Institutional Review Board Statement

This study was conducted in accordance with ethical standards for research involving human participants and was approved by the Research Ethics Committee of Universitas Islam Negeri Raden Intan Lampung, Indonesia (Protocol No. UIN-RIL/Ethics/2024/047). Informed consent was obtained from all participants, and parental or guardian consent was additionally obtained for secondary school participants under the age of 18.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Generative AI Statement

Generative AI tools were used only for language refinement and editorial assistance. The authors reviewed, verified, and take full responsibility for the accuracy, originality, and integrity of the final manuscript.

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