JURNAL ILMIAH SAINS TEKNOLOGI DAN INFORMASI
Volume 4. Nomor 2. April 2026
e-ISSN: 2964-3104; p-ISSN: 2964-3090, Hal 68-78
DOI: https://doi.org/10.59024/jiti.v4i3.2409
Tersedia: https://jurnal.alimspublishing.co.id/index.php/JITI

AI Literacy and Human AI Collaboration for Learning Benefits Among Paket B&C Students

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Abstract. Artificial intelligence (AI) literacy is often assumed to translate directly into learning benefits, yet emerging theory suggests that the quality of human-AI collaboration — not literacy alone may be the mechanism that converts competence into benefit. This gap remains largely unexamined among students in Indonesia's non-formal secondary equivalency programmes. This study develops and empirically tests a structural model examining the direct effect of AI Literacy on Learning Benefits and its indirect effect through Human-AI Collaboration among Paket B and Paket C students. Using a quantitative explanatory design with purposive sampling, data were collected from 48 students via three adapted Likert-scale instruments and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with bootstrapping. Results show that AI Literacy significantly predicted Human-AI Collaboration ($\beta = .714$, $p < .001$), and Human-AI Collaboration significantly predicted Learning Benefits ($\beta = .760$, $p < .001$), while the direct path from AI Literacy to Learning Benefits was non-significant ($\beta = -.147$, $p = .507$); the indirect effect was significant ($\beta = .542$, $p < .001$), indicating full mediation. Findings suggest AI-literacy curricula in non-formal education should be paired with explicit collaboration-oriented pedagogical support rather than technical literacy training alone.

Keywords: AI Literacy; Human-Ai Collaboration; Learning Benefits; Non-Formal Education; PLS-SEM.

1. INTRODUCTION

Artificial intelligence (AI) has moved from a peripheral computing tool to an everyday companion in how students search for information, draft assignments, and solve problems, with generative chatbots and virtual assistants now embedded in the daily study routines of Junior, secondary and post-secondary learners worldwide. This rapid diffusion has outpaced the capacity of many education systems to prepare learners to use these tools critically and productively, making the concept of AI literacy – the competencies required to understand, use, evaluate, and act ethically toward AI – a central concern for contemporary education research (Long & Magerko, 2020; Ng et al., 2021). Building on this concern, a growing body of work has proposed and validated instruments that capture AI literacy as a multidimensional construct. Wang et al. (2023) conceptualised the Artificial Intelligence Literacy Scale (AILS) around awareness, use, evaluation, and ethics, while Ng et al. (2024) extended this line of work with the AI Literacy Questionnaire (AILQ), which frames literacy through affective, behavioural, cognitive, and ethical learning dimensions validated specifically among secondary school students. At the policy level, UNESCO's AI Competency Framework for Students (Miao & Shiohira, 2024) similarly foregrounds a human-centred mindset and ethical awareness alongside technical competence, and recent scale-development work has shown that

Naskah Masuk: 25 Februari 2026; Revisi: 22 Maret 2026; Diterima: 28 April 2026; Terbit: 30 April 2026

ethical awareness itself can be deliberately cultivated and measured as students engage in AI-assisted problem-solving (Kong & Zhu, 2025).

However, being literate about AI is not the same as working with it effectively. As students increasingly rely on AI systems as thinking partners rather than passive tools, researchers have begun to theorise the quality of the human-AI relationship itself – encompassing trust, communication, shared decision-making, and genuine collaboration – as a construct distinct from literacy (Seeber et al., 2020; Järvelä et al., 2023). Instruments such as the Human-AI Trust Attitude measure (Larasati et al., 2025) and the more recent Human-AI Collaboration Dynamics Scale (Mahy & Li, 2026) operationalise this relational dimension, and education-specific work confirms that trust and collaborative fluency, rather than mere familiarity with AI tools, shape how students adopt AI-supported learning technologies (Nazaretsky et al., 2025). This suggests that AI literacy may be a necessary but insufficient condition for realising the learning benefits that AI is often assumed to deliver; the manner in which students and AI collaborate may be the mechanism that converts competence into benefit.

The learning benefits associated with AI use are typically framed around improved comprehension of material, greater learning efficiency, enhanced creativity, stronger problem-solving, and deeper reflection on one's own learning process – dimensions that build on established perceived-learning instruments (Rovai et al., 2009) and on newer, AI-specific empowerment measures such as the Empowerment in Using AI for Problem-Solving scale (Kong et al., 2025). Related evidence outside the AI-collaboration literature shows that digital and AI-related literacies are indeed associated with academic performance, but largely through general digital-competence or self-efficacy mechanisms (Zakir et al., 2025) rather than through the specific dynamics of human-AI collaboration.

Two gaps motivate the present study. First, empirical evidence on AI literacy, human-AI collaboration, and their educational consequences remains concentrated in higher-income education systems and, within Indonesia, in general junior-secondary settings (Kresnandya & Rizaldi, 2025); learners enrolled in non-formal equivalency programmes – Paket B (junior-secondary equivalency) and Paket C (senior-secondary equivalency) alike – who often study with limited direct classroom scaffolding and therefore rely more heavily on independent, AI-assisted learning, remain almost entirely unstudied. Second, while mediation models linking literacy to learning outcomes have been tested using digital-competence or self-efficacy mediators (Zakir et al., 2025), no study to date has modelled human-AI collaboration itself as the mechanism that translates AI literacy into learning benefit within a single, empirically validated structural model.

Addressing these gaps, this study aims to develop and empirically test a structural model examining (a) the effect of AI Literacy on Human-AI Collaboration, (b) the effect of Human-AI Collaboration on Learning Benefits, (c) the direct effect of AI Literacy on Learning Benefits, and (d) the mediating role of Human-AI Collaboration in the relationship between AI Literacy and Learning Benefits, among Paket B and Paket C non-formal equivalency-education students (junior- and senior-secondary levels, respectively). The study is intended to contribute theoretically by clarifying the mechanism through which AI competence translates into learning benefit, and practically by informing the design of AI-literacy curricula and collaboration-oriented pedagogical support in non-formal secondary education settings in Indonesia.

2. LITERATURE REVIEW

AI Literacy

AI literacy refers to the set of competencies that allow an individual to understand foundational AI concepts, use AI applications appropriately, evaluate their outputs critically, and act in accordance with ethical principles when engaging with these technologies (Long & Magerko, 2020; Ng et al., 2021). Across recent scale-development studies, this construct is consistently operationalised through four related dimensions: understanding what AI is and how it works, using AI tools skilfully for specific tasks, evaluating the accuracy, bias, and reliability of AI-generated output, and observing ethical norms such as proper attribution, privacy protection, and responsible use (Wang et al., 2023; Ng et al., 2024). This four-dimensional structure – understanding, use, evaluation, and ethics – is echoed in UNESCO's AI Competency Framework for Students, which positions a human-centred mindset and ethical awareness as foundations for technical competence rather than as an afterthought (Miao & Shiohira, 2024), and is reinforced by evidence that ethical awareness in AI-assisted problem-solving can be deliberately cultivated and measured among secondary and university students (Kong & Zhu, 2025).

Human-AI Collaboration

Where AI literacy describes what a person knows and can do with AI, human-AI collaboration describes how a person and an AI system work together once that competence is put into practice. Seeber et al. (2020) frame this as a teaming problem, in which humans and AI must coordinate communication, joint action, and complementary strengths to accomplish a shared task, while Järvelä et al. (2023) extend this reasoning into learning contexts through a model of human-AI shared regulation, arguing that AI can meaningfully participate in the socially shared regulatory processes that underlie collaborative learning. At the level of individual attitudes, trust has emerged as a foundational component of this relationship: validated instruments now exist to measure the extent to which users trust AI systems (Larasati et al., 2025), and education-specific evidence confirms that this trust, rather than mere exposure to AI tools, predicts students' willingness to adopt AI-supported learning technologies (Nazaretsky et al., 2025). Building on these strands, recent psychometric work operationalises human-AI collaboration dynamics more broadly across trust, communication, and joint decision-making, offering a validated multidimensional structure for measuring how students and AI systems collaborate rather than merely coexist (Mahy & Li, 2026).

Learning Benefits

The learning benefits construct captures the perceived pedagogical value that students derive from AI-assisted learning. It draws on the long-standing distinction between cognitive, affective, and psychomotor dimensions of perceived learning established in traditional and virtual classroom settings (Rovai et al., 2009), while incorporating dimensions that are more specific to AI-assisted learning, namely creativity, problem-solving, and reflection on one's own learning strategies (Kong et al., 2025). Empirical work outside the AI-collaboration literature corroborates that such benefits are attainable: digital and AI-related literacies have been linked to improved academic performance, principally through general digital-competence and self-efficacy pathways (Zakir et al., 2025). What remains underexamined is whether these benefits are better explained by literacy alone or by the quality of the collaborative process between the learner and the AI system.

Relationships Among Constructs and Hypothesis Development

Taken together, the literature suggests a plausible causal chain: literate users are better positioned to establish appropriate trust, communicate their needs clearly, and share decision-making with an AI system (Ng et al., 2021; Wang et al., 2023), and it is through this collaborative process – rather than through literacy in isolation – that learning benefits are most directly realised (Järvelä et al., 2023; Kong et al., 2025). At the same time, literate students may also derive some learning benefit directly, simply by using AI tools more effectively and evaluating their output more critically, independent of the depth of collaboration involved (Zakir et al., 2025). These relationships are formalised in the following hypotheses.

H1. AI Literacy has a positive effect on Human-AI Collaboration.

H2. Human-AI Collaboration has a positive effect on Learning Benefits.

H3. AI Literacy has a positive effect on Learning Benefits.

H4. Human-AI Collaboration mediates the effect of AI Literacy on Learning Benefits.

The conceptual model implied by these hypotheses positions AI Literacy as the exogenous construct, Human-AI Collaboration as the mediating construct, and Learning Benefits as the ultimate endogenous outcome, with both a direct path from AI Literacy to Learning Benefits and an indirect path routed through Human-AI Collaboration.

3. RESEARCH METHOD

Research Design

This study employs a quantitative, explanatory (associative) survey design intended to test causal relationships among latent constructs through a single cross-sectional data collection. This design is appropriate given the study's objective of estimating both direct and mediated effects among AI Literacy, Human-AI Collaboration, and Learning Benefits, which requires the simultaneous estimation of a multi-construct structural model rather than separate bivariate tests.

Population and Sample

The population comprises students enrolled in non-formal equivalency education programmes at Community Learning Centres (Pusat Kegiatan Belajar Masyarakat/PKBM) in Indonesia, specifically Paket B (junior-secondary equivalency, comparable to Grades 7–9) and Paket C (senior-secondary equivalency, comparable to Grades 10–12), reflecting learners who commonly engage in independent, AI-assisted study with comparatively limited direct classroom scaffolding characteristic of non-formal education settings. A minimum sample of 100 respondents is targeted to satisfy the sample-size requirements of structural equation modelling and to support subgroup analyses across the two programme levels. Given the limited and dispersed size of the accessible PKBM student population, respondents are selected through purposive sampling, with eligibility limited to Paket B and Paket C students who report having used at least one AI application (e.g., a chatbot or virtual assistant) to support their learning; where feasible, quotas are applied across the two levels so that the achieved sample is not dominated by either group.

Instrumentation

Data are collected using a self-administered questionnaire comprising the three constructs described above, each measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). AI Literacy (the exogenous construct) is measured with 20 items across four dimensions – understanding AI, using AI, evaluating AI, and AI ethics – adapted from the AI Literacy Scale (Wang et al., 2023) and the AI Literacy Questionnaire (Ng et al., 2024). Human-AI Collaboration (the mediating construct) is measured with 16 items across four dimensions – trust, communication, decision-making, and collaboration – adapted from the human-AI trust and collaboration-dynamics literature (Larasati et al., 2025; Mahy & Li, 2026) and from computer-supported collaborative learning research. Learning Benefits (the endogenous outcome construct) is measured with 15 items across five dimensions – comprehension of material, learning efficiency, creativity, problem-solving, and reflective learning – adapted from established perceived-learning and AI-empowerment scales (Rovai et al., 2009; Kong et al., 2025). Prior to full-scale data collection, all items undergo content validation by a panel of education and psychometrics experts, from which a Content Validity Ratio/Index is computed, followed by a pilot test involving 30 to 50 respondents outside the main sample to check item clarity and preliminary internal consistency.

Data Analysis Technique

Data are analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS, following the two-stage evaluation procedure recommended for reflective measurement models (Hair et al., 2019). The measurement model is first assessed for convergent validity and reliability using outer loadings, Cronbach's alpha, and composite reliability, and for discriminant validity using the average variance extracted (AVE) and the heterotrait-monotrait ratio (HTMT); variance inflation factors (VIF) are also examined to rule out collinearity among indicators. The structural model is then evaluated using the coefficient of determination (R^2), predictive relevance (Q^2), and path coefficients derived from a bootstrapping procedure, which are used to test the significance of the direct paths specified in H1 through H3. The mediating role of Human-AI Collaboration specified in H4 is tested by examining the indirect effect of AI Literacy on Learning Benefits through Human-AI Collaboration, together with the corresponding effect size (f^2), to determine whether the mediation is full or partial.

Research Model

The structural model specifies AI Literacy (denoted X) as the exogenous latent construct, Human-AI Collaboration (denoted M) as the mediating latent construct, and Learning Benefits (denoted Y) as the endogenous outcome construct. The model estimates a direct path from X to M, a direct path from M to Y, a direct path from X to Y, and an indirect path from X to Y through M, corresponding respectively to H1, H2, H3, and H4.

Ethical Considerations

Because a portion of the target population (Grade 7–12 students) is under the age of 18, data collection procedures include parental or guardian consent in addition to student assent, alongside standard protections of voluntary participation, informed consent, and respondent anonymity, consistent with accepted ethical standards for educational research involving minors.

4. RESULTS and DISCUSSION

Data Collection and Respondent Profile

Data were collected between 25 and 31 July 2026 using three self-administered Google Form questionnaires (AI Literacy, Human-AI Collaboration, and Learning Benefits) distributed to Paket B and Paket C students at PKBM ABhome, Kota Bogor, Indonesia. After removing duplicate submission and matching respondents across the three instruments, N = 48 students with complete responses on all three constructs were retained for analysis (age range 13–25 years, M = 15.9, Mdn = 16), consistent with the combined Paket B–Paket C population targeted in this study.

Measurement Model (Outer Model) Assessment

Following the two-stage evaluation procedure (Hair, Risher, Sarstedt, & Ringle, 2019), indicators with an outer loading below 0.40 were removed prior to structural model estimation: three AI Literacy items (evaluating- and using-AI indicators) and three Human-AI Collaboration – Trust indicators. Table 1 summarises the resulting measurement model.

Table 1. Reliability and Convergent Validity of the Measurement Model.

Construct	Items (retained/total)	Cronbach's α	CR (ρc)	AVE
AI Literacy (X)	17 / 20	0.906	0.918	0.404
Human-AI Collaboration (M)	13 / 16	0.835	0.870	0.344
Learning Benefits (Y)	15 / 15	0.899	0.915	0.423

Internal consistency reliability was strong for all constructs (α and CR $\geq$ 0.83), but average variance extracted (AVE) remained below the 0.50 benchmark for all three constructs even after item purification.

Rather than removing further items – which would compromise content coverage of the sub-dimensions – this is reported as a genuine convergent-validity limitation of the adapted instruments in this sample (see Discussion). Discriminant validity was nonetheless supported: the heterotrait-monotrait ratio (HTMT) was well below the 0.90 threshold for every construct pair (Table 2), and inner VIF for the two predictors of Learning Benefits was 2.04, indicating no problematic collinearity.

Table 2. Discriminant Validity (HTMT).

Construct pair	HTMT
AI Literacy ↔ Human-AI Collaboration	0.800
AI Literacy ↔ Learning Benefits	0.420
Human-AI Collaboration ↔ Learning Benefits	0.732

Structural Model and Hypothesis Testing

The structural model explained a moderate-to-substantial proportion of variance in Human-AI Collaboration ($R^2 = 0.509$) and a moderate proportion in Learning Benefits ($R^2 = 0.440$); both endogenous constructs showed positive predictive relevance ($Q^2_x = 0.138$; $Q^2_\gamma = 0.032$). Path coefficients were tested via bootstrapping (5,000 resamples; Table 3).

Table 3. Structural Path Coefficients and Hypothesis Testing (Bootstrap, B = 5,000).

Hyp.	Path	β	SE	t	p	Decision
H1	AI Literacy → Human-AI Collaboration	0.714	0.072	9.97	0.000	Supported
H2	Human-AI Collaboration → Learning Benefits	0.760	0.160	4.74	0.000	Supported
H3	AI Literacy → Learning Benefits (direct)	-0.147	0.221	-0.66	0.507 (ns)	Not supported
H4	AI Literacy → Collaboration → Learning Benefits (indirect)	0.542	0.146	3.71	0.000	Supported

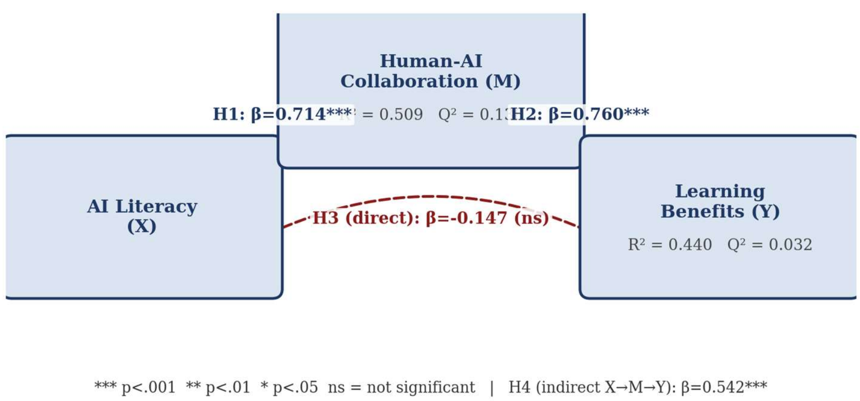

Figure 2. Estimated structural model with bootstrapped path coefficients.

H1, H2, and H4 were supported; H3 was not. Because the direct effect of AI Literacy on Learning Benefits was non-significant while the indirect effect through Human-AI Collaboration was significant, the pattern corresponds to full (indirect-only) mediation (Zhao, Lynch, & Chen, 2010): AI Literacy influences Learning Benefits entirely through the quality of the collaborative relationship students build with AI, not through literacy in isolation.

Discussion

The strong AI Literacy → Human-AI Collaboration path (H1) corroborates the theoretical claim that literate users are better positioned to calibrate trust, communicate intent, and share decision-making with an AI system (Long & Magerko, 2020; Ng, Wu, Leung, Chiu, & Chu, 2024; Wang, Rau, & Yuan, 2023). The large effect of Human-AI Collaboration on Learning Benefits (H2) is consistent with Seeber et al. (2020) and Järvelä, Nguyen, and Hadwin (2023), who argue that treating AI as a coordinating teammate – rather than a passive tool – is what converts capability into shared learning outcomes, and echoes Mahy and Li's (2026) argument that collaboration dynamics, not mere tool exposure, drive value from generative AI use.

The non-significant direct path (H3) together with the significant indirect path (H4) is this study's central finding: AI Literacy alone was not sufficient to predict Learning Benefits among Paket B and Paket C students; benefit only emerged when literacy translated into genuine collaboration. This mirrors Nazaretsky, Mejia-Domenzain, Swamy, Frej, and Käser's (2025) finding that trust – not mere exposure – predicts students' adoption of AI-supported learning technologies, and reinforces this study's motivating premise that human-AI collaboration, rather than AI literacy in isolation, is the operative mechanism through which competence becomes benefit.

The below-threshold AVE for all three constructs warrants caution. Notably, all four retained Trust indicators loaded weakly; the source instrument (Larasati, De Liddo, & Motta, 2025) was originally validated among adult, non-expert users evaluating AI in medical decision-support contexts, and its items may require further contextual adaptation before they cleanly capture adolescent PKBM students' trust in everyday learning-support AI. Future revisions should prioritise re-wording or replacing the weakest Trust and Using-AI items identified here.

Limitations include the pilot-scale sample (N = 48, below the planned minimum of 100), the absence of a programme-level indicator distinguishing Paket B from Paket C respondents – which prevented the planned subgroup analysis – and the single cross-sectional measurement occasion. Continued data collection with a programme-level item and a larger purposive sample is recommended before final conclusions are drawn.

5. CONCLUSION

This study aimed to clarify how AI Literacy translates into Learning Benefits among Paket B and Paket C students by testing both its direct effect and its indirect effect through Human-AI Collaboration. The structural model results support this aim: AI Literacy significantly strengthened Human-AI Collaboration, and Human-AI Collaboration in turn significantly enhanced Learning Benefits, while the direct path from AI Literacy to Learning Benefits was not significant. This pattern indicates that AI Literacy's influence on Learning Benefits is transmitted entirely through the quality of the collaborative relationship students build with AI, rather than through literacy in isolation — confirming H1, H2, and H4, and disconfirming H3.

Practically, this implies that AI-literacy programmes in non-formal secondary equivalency education should not stop at building technical competence; they should be paired with explicit instruction in collaborative practices such as trust calibration, clear communication with AI systems, and shared decision-making, since these appear to be what ultimately convert literacy into learning benefit. These conclusions should nonetheless be read with caution: the sample was pilot-scale (48 of the planned minimum of 100 respondents), convergent validity (AVE) for all three constructs fell below the conventional threshold despite acceptable reliability, and the absence of a programme-level indicator prevented the planned comparison between Paket B and Paket C students.

Future research should therefore prioritise reaching the targeted sample size, revising the weaker-loading items identified in this study — particularly within the Trust dimension of the Human-AI Collaboration scale — and collecting programme-level data to enable subgroup analysis, ideally within a longitudinal design that can track how AI literacy and collaboration develop over the course of a PKBM programme.

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