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Enhancing Vocational Students' Socio-Emotional Adjustment through Artificial Intelligence Supported Learning

Sari Indrayani [1] and Rita Nur Anjani [2]

[1]Sekolah Menengah Kejuruan Negeri 02 Banjit, Indonesia
[2]Universitas Islam Negeri Raden Intan Lampung, Indonesia

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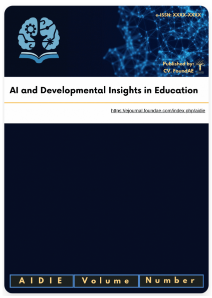
Abstract

Artificial intelligence (AI) is increasingly embedded in school learning environments, yet evidence remains limited on its developmental value in vocational secondary education. This quasi-experimental study examined whether an eight-week AI-supported socio-emotional learning and AI literacy intervention was associated with improved socio-emotional adjustment, AI literacy, and perceived AI support among vocational students. A non-equivalent pretest-posttest control-group design was implemented with 168 Grade 10–11 students from four intact classes in two public vocational schools in Way Kanan, Indonesia. The AI-supported condition ($n = 84$) received activities integrating AI literacy, reflective prompting, feedback evaluation, peer dialogue, and teacher-mediated socio-emotional reflection, while the comparison condition ($n = 84$) received regular technology-enriched instruction. ANCOVA controlling for pretest scores showed higher adjusted posttest scores in the AI-supported condition for socio-emotional adjustment, $F(1,165) = 18.72$, $p < .001$, partial $\eta^2 = .102$; AI literacy, $F(1,165) = 44.96$, $p < .001$, partial $\eta^2 = .214$; and perceived AI support, $F(1,165) = 16.84$, $p < .001$, partial $\eta^2 = .093$. Findings suggest that structured, teacher-guided AI learning may support vocational students' socio-emotional and AI-related development, although intact-class assignment and self-report outcomes require cautious interpretation.

Keywords: artificial intelligence in education; socio-emotional adjustment; vocational high school

Corresponding Author:
Sari Indrayani
Email: sariindrayani887@gmail.com
https://orcid.org/0009-0001-4656-5424



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Introduction

Artificial intelligence has moved from a peripheral educational technology into a visible component of learning infrastructures, including adaptive platforms, automated feedback systems, conversational agents, learning analytics, and generative AI tools. Recent syntheses show rapid expansion of AI research in education, but they also indicate that the dominant evidence base remains concentrated on learning performance, assessment, efficiency, higher education, and implementation policy rather than on students' developmental functioning in secondary classrooms (Bond et al., 2024; Chiu et al., 2023; Crompton & Burke, 2023; Ng et al., 2023a; Yim & Su, 2025). This imbalance matters because students encounter AI within peer groups, classroom expectations, emotional challenges, and emerging identities as learners and future workers, not in purely cognitive spaces.

The current generation of AI tools is not merely a set of static digital resources. Many systems respond conversationally, generate personalized explanations, offer feedback, and shape how students ask for help, evaluate their own work, and collaborate with peers. Recent studies on ChatGPT and related tools suggest that learners often perceive generative AI as useful for feedback, writing, inquiry, and problem solving, while also recognizing risks related to inaccuracy, over-reliance, privacy, bias, academic integrity, and weakened human judgment (Baek et al., 2024; Chiu, 2024; Farhi et al., 2023; Kasneci et al., 2023; Tlili et al., 2023). These risks are relevant to socio-emotional adjustment because they affect confidence regulation, trust, help-seeking, peer interaction, and responsible learning habits.

A parallel body of research on digital technology and adolescent wellbeing cautions against deterministic interpretations in which technology is treated as uniformly beneficial or harmful. Recent reviews and empirical work show that psychological and social consequences vary according to intensity, purpose, learner vulnerability, social context, and adult mediation (Chen et al., 2024; Limone & Toto, 2022; Piccerillo & Digennaro, 2025; Şahin et al., 2025). The educational question is therefore not whether AI is inherently good or bad for students. A sharper question is whether structured, pedagogically bounded AI use can support socio-emotional adjustment more effectively than ordinary technology use that lacks explicit AI literacy, reflective scaffolding, and teacher mediation.

This issue is particularly relevant for vocational high schools. Students in vocational programs are expected to develop technical competence while also strengthening workplace-relevant social and emotional capacities, including self-management, communication, teamwork, feedback responsiveness, ethical judgment, and confidence in solving authentic problems. In rural and semi-rural regencies such as Way Kanan, AI integration may offer opportunities for personalized support and simulated practice, but it may also widen inequalities if students receive access without systematic guidance. A vocational classroom therefore provides a consequential setting for examining whether AI-supported learning can be organized around socio-emotional as well as academic purposes.

AI literacy has increasingly been positioned as a necessary condition for responsible AI engagement. It includes understanding basic AI concepts, using AI tools appropriately, evaluating AI outputs critically, and recognizing social and ethical implications (Laupichler et al., 2022; Ng et al., 2024; Southworth et al., 2023). K-12 AI literacy research shows that students often hold misconceptions about AI, including assumptions that AI is automatically objective, omniscient, or ethically neutral (Bewersdorff et al., 2023; Kim et al., 2023). Other studies demonstrate that structured AI learning activities can improve students' conceptual understanding, ethical awareness, and confidence when designed with age-appropriate tasks and teacher support (Hong & Kim, 2025; Ottenbreit-Leftwich et al., 2023; Zhang et al., 2023).

Human-AI collaboration scholarship further clarifies why AI-supported socio-emotional learning should be designed as a teacher-guided process rather than as unrestricted tool access. Hybrid human-AI perspectives emphasize that AI is most educationally defensible when it augments teacher and learner agency instead of replacing human interpretation (Järvelä et al., 2023; Molenaar, 2022). Studies of AI-supported feedback and collaborative learning show that AI can contribute to feedback literacy, peer review quality, and group regulation, yet these benefits depend on task structure, transparency, and students' ability to interpret automated support critically (Darvishi et al., 2022; Guo et al., 2025; Ji et al., 2023). For socio-emotional outcomes, AI should therefore function as a structured prompt for reflection, dialogue, and responsible decision making, not as an autonomous counselor or substitute teacher.

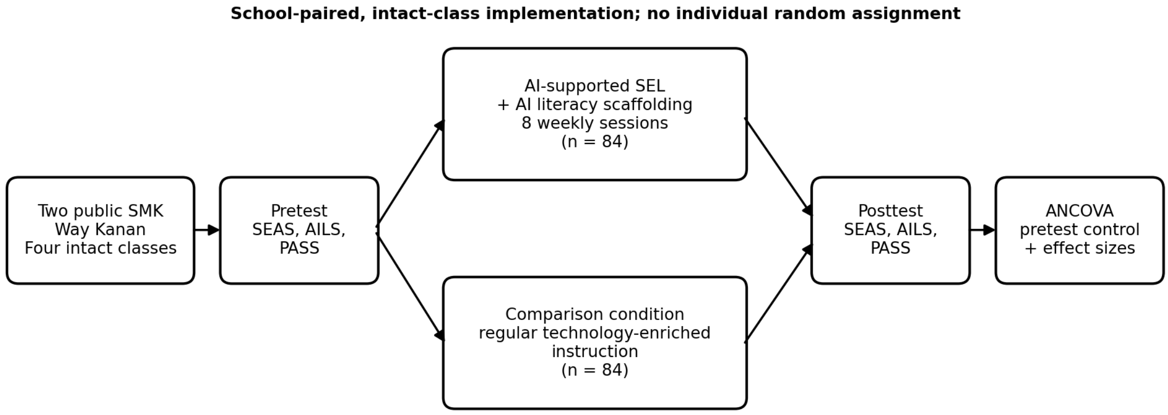
The available evidence leaves several unresolved problems. First, recent AI-in-education research continues to prioritize cognitive or performance indicators, while adolescent socio-emotional adjustment remains less frequently examined as an intervention outcome. Second, AI literacy is often studied as a standalone competency rather than as a scaffold within interventions designed to support broader developmental outcomes. Third, much empirical work is descriptive, cross-sectional, or higher-education oriented, leaving limited quasi-experimental evidence from secondary school classrooms. Fourth, evidence from Indonesian vocational schools remains scarce, even though AI adoption intersects with local infrastructure, teacher readiness, school culture, and students' preparation for work and further study.

The present study responds to these problems by testing an eight-week AI-supported socio-emotional learning and AI literacy intervention in vocational high school classrooms in Way Kanan, Indonesia. The intervention integrated generative AI use with explicit AI literacy, prompt evaluation, peer dialogue, teacher-mediated reflection, and ethical decision-making activities. The study examined whether students in the AI-supported condition showed greater posttest outcomes than comparison students in socio-emotional adjustment, AI literacy, and perceived AI support after pretest differences were statistically controlled. Because intact classes were used, the study is framed as a quasi-experiment; the design strengthens temporal interpretation compared with a cross-sectional survey but does not provide the same level of causal certainty as individual random assignment.

Three hypotheses guided the study. H1: students in the AI-supported condition would show higher posttest socio-emotional adjustment than students in the comparison condition after controlling for pretest scores. H2: students in the AI-supported condition would show higher posttest AI literacy than comparison students after controlling for pretest scores. H3: students in the AI-supported condition would show higher posttest perceived AI support than comparison students after controlling for pretest scores.

Figure 1 summarizes the pretest-posttest logic used in the study. The diagram clarifies that both conditions completed the same measurement schedule, while only the AI-supported classes received structured AI literacy and socio-emotional reflection activities during the eight-week intervention.

Figure 1
Pretest-posttest non-equivalent control-group design implemented in vocational classrooms in Way Kanan.



Note. *SEAS = Socio-Emotional Adjustment Scale; AILS = AI Literacy Scale; PASS = Perceived AI Support Scale. Intact classes, not individual students, were assigned to conditions.*

The design represented in Figure 1 positions AI as a classroom scaffold embedded within teacher-guided learning, not as a standalone developmental treatment. This distinction guided the interpretation of the results and helped avoid claims that technology exposure alone accounted for observed group differences.

Methods

Research Design

This study used a quantitative quasi-experimental pretest-posttest non-equivalent control-group design. The design was selected because the participating schools required intact class participation and did not permit individual random assignment. Each school contributed one AI-supported class and one comparison class of similar grade level, which reduced but did not eliminate school-level and teacher-level confounding. The primary analytic strategy compared posttest outcomes between conditions while statistically controlling for corresponding pretest scores.

Participants and Setting

Participants were 168 vocational high school students enrolled in Grade 10 and Grade 11 at two public vocational high schools (SMK) in Way Kanan Regency, Lampung Province, Indonesia. The AI-supported condition included 84 students and the comparison condition included 84 students. Students ranged in age from 15 to 18 years ($M = 16.4$, $SD = 0.82$). The sample included 91 female students (54.2%) and 77 male students (45.8%). All participating classes used digital learning resources during ordinary instruction, but only the experimental classes received structured AI-supported socio-emotional learning activities during the intervention period.

Intervention

The intervention lasted eight weeks and was implemented during regular technology-enriched vocational learning sessions. Each weekly session combined three elements: (a) an AI literacy focus, such as identifying hallucinations, bias, privacy risks, or effective prompting; (b) a socio-emotional learning task, such as self-management reflection, feedback interpretation, perspective taking, or responsible decision making; and (c) a collaborative activity in which students used AI-generated prompts or feedback as a starting point for peer dialogue and teacher-guided reflection. Students were explicitly instructed that AI tools were learning aids rather than authorities or substitutes for teachers, peers, or professional psychological support.

Implementation Control and Fidelity

To reduce implementation drift, participating teachers used a common session guide specifying weekly objectives, example prompts, peer-discussion rules, and safety reminders. Teachers remained responsible for selecting classroom examples, interpreting AI outputs, moderating discussion, and correcting inaccurate or inappropriate responses. The comparison classes were taught during the same academic period and followed the same general vocational learning themes, but they did not receive structured AI literacy modules or AI-supported reflection tasks before posttest. To reduce inequity, comparison classes were offered access to the AI-literacy materials after data collection was completed.

Comparison Condition

Comparison classes continued regular technology-enriched instruction using teacher explanations, worksheets, learning management system activities, online searches, and peer discussion. They did not receive structured AI literacy modules, AI-supported reflective prompts, or teacher-guided AI output evaluation during the intervention period. This condition was selected to compare structured AI-supported learning against the type of digital instruction already present in the schools.

Measures

Socio-emotional adjustment was the primary outcome and was measured using an adapted 15-item scale covering peer relations, emotional regulation, and prosocial engagement. Item development was informed by recent adolescent SEL measurement literature and the structure of socio-emotional competence domains in secondary education (Fernández-Martín et al., 2022; Şahin et al., 2025). AI literacy was measured using a 12-item adapted scale representing conceptual understanding, operational use, critical evaluation, and ethical awareness, informed by recent AI literacy frameworks and K-12 AI education research (Laupichler et al., 2022; Ng et al., 2024; Southworth et al., 2023; Zhang et al., 2023). Perceived AI support was measured with a 10-item scale assessing whether students perceived AI-supported activities as useful, responsive, understandable, and supportive of learning. All items used a 5-point Likert format from 1 (strongly disagree) to 5 (strongly agree). Instruments were translated and contextually adapted for Indonesian vocational students through bilingual review, expert judgment, and a pilot administration with students outside the analytic sample.

Data Collection Procedures

Pretest data were collected one week before the intervention and posttest data were collected within one week after the final session. Trained research assistants administered the instruments during regular class periods using school-approved digital forms. Participation was voluntary, and students were reminded that survey responses would not influence grades or teacher evaluation. The final analytic dataset contained less than 2% missing item-level data, which were handled using scale-level mean substitution when at least 80% of items on a scale had been completed.

Data Analysis

Baseline equivalence was examined using descriptive comparisons and independent-samples tests for pretest variables. The main hypotheses were tested using analysis of covariance (ANCOVA), with posttest scores as dependent variables, condition as the fixed factor, and corresponding pretest scores as covariates. Before interpreting ANCOVA results, models were screened for homogeneity of regression slopes, residual normality, outliers, and homogeneity of variance. Partial eta squared was used as the effect size index, and 95% confidence intervals were reported for adjusted mean differences. Gain scores were reported descriptively to aid interpretation, but inferential conclusions were based on covariate-adjusted posttest comparisons. All analyses were interpreted conservatively because intact classes were used.

Ethical Considerations

Ethical approval was granted by the Research Ethics Committee of UIN Raden Intan Lampung. Permission was obtained from participating schools. Written informed consent was obtained from parents or guardians, and written assent was obtained from students before data collection. Student data were anonymized before analysis, and no personally identifying information was included in the dataset used for reporting. AI was not used to provide diagnosis, counseling, or individualized psychological advice.

All 168 students who completed the pretest were retained for posttest analysis. Missing item-level responses were minimal and did not exceed 2% on any scale. Baseline comparisons reported in Table 1 suggested that the two conditions were similar on age, gender distribution, grade level, and pretest values for the main study variables.

Table 1 presents the sample profile and pretest equivalence information. Reporting these characteristics is necessary because the study used intact classes, making baseline comparability an important condition for cautious interpretation of post-intervention differences.

Table 1

Participant characteristics and baseline equivalence by condition.

Characteristic / baseline variable	AI-supported condition (n = 84)	Comparison condition (n = 84)	Test statistic	p
Age, M (SD)	16.43 (0.81)	16.38 (0.83)	$t = 0.40$	.688
Female students, n (%)	47 (56.0%)	44 (52.4%)	$\chi^2 = 0.22$	.640
Grade 10, n (%)	42 (50.0%)	41 (48.8%)	$\chi^2 = 0.02$	.877
SEAS pretest, M (SD)	3.28 (0.52)	3.31 (0.54)	$t = -0.37$	.711
AI literacy pretest, M (SD)	2.89 (0.58)	2.91 (0.57)	$t = -0.23$	.821
Perceived AI support pretest, M (SD)	3.02 (0.61)	3.01 (0.60)	$t = 0.11$	.912

Note. *SEAS = Socio-Emotional Adjustment Scale. Baseline comparisons did not identify statistically significant pretest differences between conditions on the reported characteristics.*

The baseline pattern in Table 1 supports the use of covariate-adjusted posttest analysis, although it does not eliminate all selection threats that can occur in quasi-experimental classroom research. For this reason, the study reports intervention-associated differences rather than unrestricted causal claims.

Table 2 reports the reliability and descriptive range of the instruments used for pretest and posttest measurement. These estimates indicate whether the scales were sufficiently consistent for group-level comparison in the present sample.

Table 2

Psychometric properties of study instruments.

Scale / subscale	Items	Pretest α	Posttest α	Observed range
SEAS total	15	.88	.90	1.40-5.00
Peer relations	5	.80	.83	1.20-5.00
Emotional regulation	5	.82	.85	1.40-5.00
Prosocial engagement	5	.79	.82	1.20-5.00
AI literacy	12	.86	.88	1.17-5.00
Perceived AI support	10	.84	.86	1.20-5.00

Note. *Cronbach alpha coefficients are reported separately for pretest and posttest administrations. Values above .70 were considered acceptable for the present group-level analyses.*

As shown in Table 2, all scales demonstrated acceptable internal consistency at both measurement occasions. The reliability estimates support the planned ANCOVA analyses while recognizing that all measures remained self-report indicators.

Results

Table 3 summarizes pretest, posttest, and gain-score patterns for the primary and secondary outcomes. The table is intended to show the magnitude and direction of change before inferential ANCOVA results are presented.

Table 3

Pretest-posttest descriptive statistics by condition.

Outcome	Condition	Pretest M (SD)	Posttest M (SD)	Mean gain
SEAS total	AI-supported	3.28 (0.52)	3.76 (0.50)	0.48
SEAS total	Comparison	3.31 (0.54)	3.43 (0.55)	0.12
Peer relations	AI-supported	3.25 (0.57)	3.68 (0.55)	0.43
Peer relations	Comparison	3.27 (0.56)	3.39 (0.57)	0.12
Emotional regulation	AI-supported	3.29 (0.58)	3.82 (0.54)	0.53
Emotional regulation	Comparison	3.32 (0.59)	3.47 (0.58)	0.15
Prosocial engagement	AI-supported	3.30 (0.61)	3.78 (0.57)	0.48
Prosocial engagement	Comparison	3.34 (0.60)	3.43 (0.61)	0.09
AI literacy	AI-supported	2.89 (0.58)	3.67 (0.55)	0.78
AI literacy	Comparison	2.91 (0.57)	3.12 (0.58)	0.21
Perceived AI support	AI-supported	3.02 (0.61)	3.58 (0.59)	0.56

Outcome	Condition	Pretest M (SD)	Posttest M (SD)	Mean gain
Perceived AI support	Comparison	3.01 (0.60)	3.17 (0.62)	0.16

Note. *Gain scores are descriptive and were calculated as posttest minus pretest. Inferential conclusions were based on ANCOVA models controlling for corresponding pretest scores.*

The descriptive results in Table 3 show larger gains in the AI-supported condition across socio-emotional adjustment, AI literacy, and perceived AI support. The largest descriptive improvement occurred for AI literacy, which is consistent with the explicit literacy component of the intervention.

Before ANCOVA results were interpreted, assumption checks were examined. No model showed evidence of a serious violation of the homogeneity-of-regression-slopes assumption, and residual screening did not identify influential outliers requiring removal. These checks do not remove the limitations of intact-class assignment, but they support the use of ANCOVA for the reported comparisons.

Table 4 presents the covariate-adjusted posttest comparisons used to test the hypotheses. Each model controlled for the corresponding pretest score, so the reported differences represent adjusted posttest contrasts rather than raw gain-score tests.

Table 4
ANCOVA results for adjusted posttest outcomes.

Outcome	Adjusted M AI-supported	Adjusted M comparison	Adjusted mean difference [95% CI]	F(1,165)	p	partial η²
SEAS total	3.75	3.44	0.31 [0.17, 0.45]	18.72	< .001	.102
Peer relations	3.67	3.40	0.27 [0.12, 0.42]	12.58	.001	.071
Emotional regulation	3.81	3.48	0.33 [0.19, 0.47]	22.31	< .001	.119
Prosocial engagement	3.77	3.44	0.33 [0.16, 0.50]	14.06	< .001	.079
AI literacy	3.66	3.13	0.53 [0.37, 0.69]	44.96	< .001	.214
Perceived AI support	3.57	3.18	0.39 [0.20, 0.58]	16.84	< .001	.093

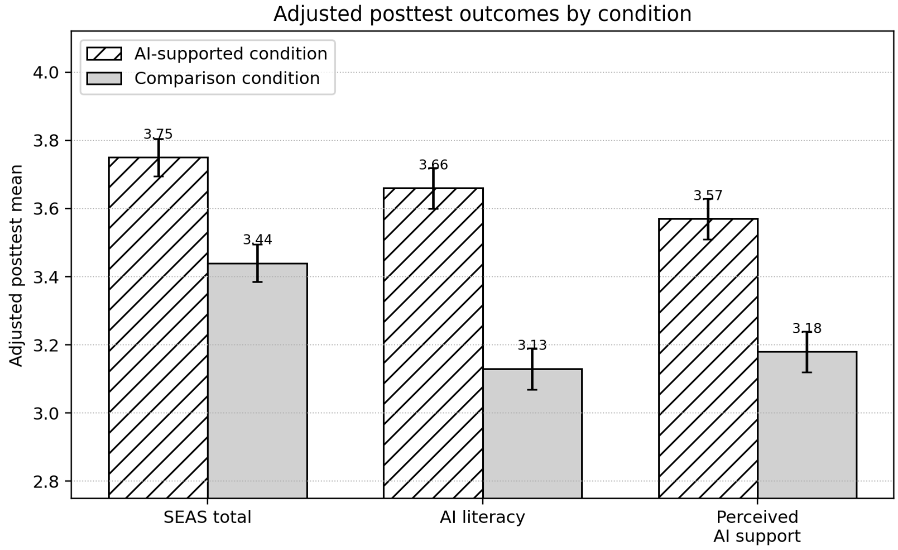
Note. *Adjusted means are estimated marginal means from ANCOVA models controlling for corresponding pretest values. Confidence intervals refer to adjusted mean differences. Partial eta-squared values indicate the proportion of the adjusted outcome variance associated with the condition.*

The ANCOVA results in Table 4 support H1, H2, and H3. The AI-supported condition showed higher adjusted posttest socio-emotional adjustment, stronger AI literacy, and greater perceived AI support than the comparison condition. The largest adjusted difference was observed for AI literacy, while the socio-emotional adjustment difference was moderate in practical magnitude.

Figure 2 visualizes the adjusted posttest means for the three main outcomes. The visual display helps readers compare the overall pattern of group differences while retaining the inferential results in Table 4 as the primary statistical evidence.

Figure 2

Adjusted posttest means for socio-emotional adjustment, AI literacy, and perceived AI support by condition.



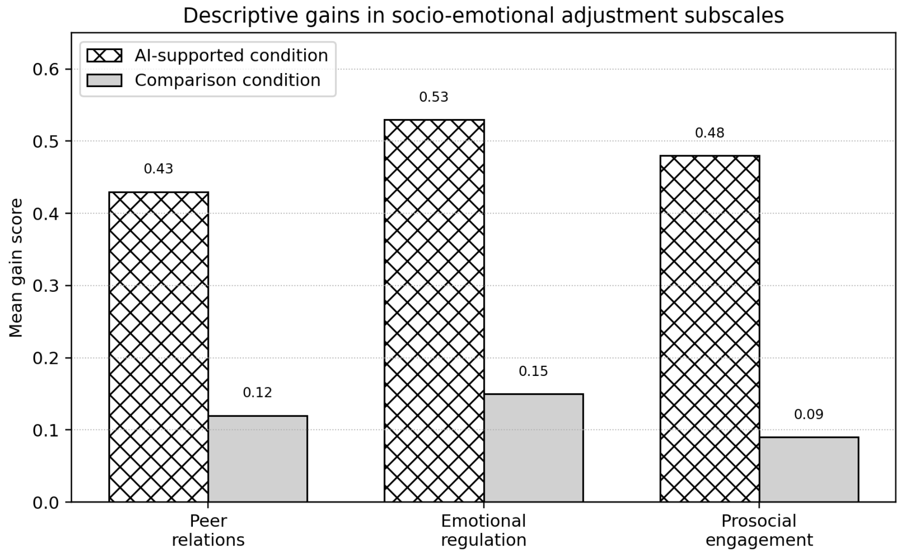
Note. *Error bars represent standard errors around adjusted posttest means. Values are based on ANCOVA models controlling for pretest scores.*

The pattern in Figure 2 indicates higher adjusted posttest scores in the AI-supported condition across all three outcomes. This pattern is consistent with the intervention design, which combined AI use with explicit literacy instruction and socio-emotional reflection.

Figure 3 provides a more detailed view of the socio-emotional adjustment subscales. This figure was included because total-score improvement can obscure whether gains are concentrated in one domain or distributed across peer relations, emotional regulation, and prosocial engagement.

Figure 3

Mean gain scores for socio-emotional adjustment subscales by condition.



Note. *Gain scores are descriptive and should be interpreted alongside the ANCOVA results in Table 4.*

The subscale gains in Figure 3 suggest that the intervention-associated improvement was not limited to a single socio-emotional domain. The largest descriptive gain appeared in emotional regulation, which is plausible because the intervention repeatedly asked students to evaluate AI feedback, manage uncertainty, and reflect before responding to peers or automated outputs.

Discussion

This quasi-experimental study examined whether structured AI-supported socio-emotional learning and AI literacy scaffolding were associated with improved outcomes among vocational students in Way Kanan. The results supported all three hypotheses. Students in the AI-supported condition showed higher adjusted posttest socio-emotional adjustment than comparison students, and they also showed stronger AI literacy and perceived AI support. These findings extend recent AI-in-education scholarship by moving beyond cross-sectional perceptions and testing a classroom intervention in a secondary vocational context.

The socio-emotional adjustment finding should be interpreted in terms of structured pedagogy rather than AI exposure alone. The intervention did not simply provide students with access to generative AI. It required students to question AI outputs, discuss feedback with peers, evaluate uncertainty, and reflect on responsible decision making under teacher guidance. This design aligns with hybrid human-AI perspectives, which argue that AI has greater educational value when it augments human agency and social regulation rather than automating judgment (Järvelä et al., 2023; Molenaar, 2022). The finding also resonates with emerging work on AI technologies for socio-emotional learning, which suggests that AI may support reflection and practice when embedded in ethically designed learning environments (Henriksen et al., 2025; Sethi & Jain, 2024).

The improvement in AI literacy was the strongest adjusted outcome. This pattern is expected because AI literacy was an explicit intervention component, but it remains substantively important. Recent K-12 AI education studies show that students may enter AI learning with misconceptions about data, automation, algorithmic authority, and ethical neutrality (Bewersdorff et al., 2023; Kim et al., 2023; Ng et al., 2024). The intervention addressed these issues through repeated evaluation of AI-generated responses, prompt revision, and discussion of bias and privacy. The results are therefore consistent with studies showing that age-appropriate AI literacy activities can improve students' conceptual and ethical understanding (Hong & Kim, 2025; Ottenbreit-Leftwich et al., 2023; Zhang et al., 2023).

The findings have a specific implication for vocational education. SMK students are preparing for workplaces in which AI-enabled tools are increasingly relevant to communication, documentation, problem solving, and decision support. Socio-emotional adjustment in this context is connected to feedback responsiveness, teamwork, ethical tool use, and confidence in technology-mediated tasks. The results suggest that AI activities may contribute to these capacities when teachers frame AI outputs as prompts for reflection and collaboration rather than as ready-made answers. This distinction is important because unstructured use of AI can also foster dependence, superficial engagement, and overconfidence in generated content (Baek et al., 2024; Farhi et al., 2023; Kasneci et al., 2023; Tlili et al., 2023).

Perceived AI support also improved more strongly in the AI-supported condition. This suggests that students' perceptions of usefulness and responsiveness may be shaped by instructional design, not only by tool features. When AI was integrated with clear goals, teacher explanation, and peer discussion, students may have experienced the tools as more understandable and supportive. This interpretation is consistent with work on AI-supported feedback and peer review, where the educational value of AI depends on how learners interpret, revise, and act on automated support (Darvishi et al., 2022; Guo et al., 2025; Ji et al., 2023).

The study also reinforces the need for ethical and human-centered safeguards. Students were minors, and the intervention involved AI-mediated reflection on social and emotional learning. AI was therefore not positioned as a counselor, emotional diagnostician, or independent authority. Teacher moderation, privacy protection, and human interpretation were treated as essential design principles. This approach is consistent with recent ethical frameworks for AI in education, which emphasize transparency, accountability, data protection, fairness, and human oversight (Holmes et al., 2022; Nguyen et al., 2023).

Several limitations should temper interpretation. First, the study used intact classes, so unmeasured classroom or teacher differences may have contributed to the results despite baseline comparability and pretest control. Second, the number of class clusters was small, making multilevel estimation impractical; therefore, the statistical models should be read as student-level ANCOVA models with cautious interpretation of classroom-level assignment. Third, the intervention was implemented in two SMK settings within one regency, so the findings should not be generalized automatically to all Indonesian vocational schools. Fourth, the outcomes were measured through self-report scales, which may be affected by social desirability, novelty effects, and students' expectations about AI. Fifth, the intervention combined AI literacy, generative AI use, peer dialogue, and teacher-guided reflection, so the design does not isolate which component produced the strongest contribution. Sixth, the eight-week duration does not show whether effects persist after structured scaffolding is removed.

For practice, the results suggest that schools should avoid introducing AI tools as neutral productivity aids without pedagogical framing. AI integration in SMK classrooms should include explicit AI literacy, structured prompting protocols, critique of inaccurate outputs, peer discussion norms, teacher-led reflection, and clear rules for privacy and academic integrity. For policymakers and school leaders, the study points to the importance of professional development that prepares teachers to connect AI literacy with socio-emotional learning and vocational competencies rather than treating AI as a purely technical innovation (Ng et al., 2023b; Ng et al., 2024).

Directions for Future Research

Future research should replicate this study using cluster-randomized or matched-school designs with larger samples across multiple Indonesian provinces. Such designs would reduce selection threats, allow appropriate modeling of classroom-level clustering, and provide stronger evidence about whether AI-supported socio-emotional learning produces reliable benefits across different school conditions.

Longitudinal follow-up is also needed. Future studies should measure whether gains in socio-emotional adjustment and AI literacy persist several months after the intervention and whether students continue to use AI tools responsibly when teacher scaffolding is reduced. Cross-lagged or growth-curve designs could clarify whether AI literacy predicts later socio-emotional adjustment or whether socio-emotionally adjusted students benefit more from AI literacy instruction.

Subsequent studies should disaggregate intervention components. Comparative designs could test AI literacy only, AI-supported reflection only, peer dialogue only, and combined models to determine which elements are necessary and which are supplementary. This would help schools adopt efficient designs without assuming that all AI-supported activities have equal value.

Future work should also incorporate richer data sources, including teacher ratings, classroom observation, peer nominations, learning analytics logs, AI prompt histories, and qualitative interviews. These data would help determine how students actually interact with AI and whether improvements in self-report scales correspond to observable changes in communication, self-management, and peer collaboration.

Research in vocational education should examine program-specific differences. AI-supported socio-emotional learning may operate differently in technology, business, health, hospitality, agriculture, and creative-industry programs. Future studies should therefore test how vocational identity, workplace simulation, local industry needs, and rural-urban infrastructure shape the developmental value and risks of AI-supported learning.

Conclusion

This study provides quasi-experimental evidence consistent with the view that structured AI-supported socio-emotional learning and AI literacy scaffolding are associated with improved socio-emotional adjustment among vocational high school students in Way Kanan, Indonesia. Compared with regular technology-enriched instruction, the AI-supported condition showed higher adjusted posttest scores for socio-emotional adjustment, AI literacy, and perceived AI support. The findings suggest that AI may have developmental value in vocational classrooms when its use is embedded in explicit literacy instruction, collaborative reflection, teacher guidance, and ethical safeguards. At the same time, the non-equivalent group design, reliance on self-report, small number of class clusters, and geographically bounded sample require cautious interpretation. The central implication is not that AI access alone improves students' socio-emotional adjustment, but that carefully scaffolded, human-centered AI pedagogy may support both responsible AI literacy and socio-emotional growth in vocational education.

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Informed Consent Statement

Written informed consent was obtained from parents or guardians, and written assent was obtained from all participating students before data collection.

Data Availability Statement

The datasets used and/or analyzed during the current study are not publicly available because the participants were minors and the consent documents did not authorize open data sharing. De-identified data may be made available from the corresponding author upon reasonable request and subject to institutional approval.

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 to support language editing, structural consistency checking, and citation-format review. The authors reviewed, verified, and approved the final manuscript and remain responsible for its content.

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