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Enhancing Four-Dimensional Student Engagement Through Teacher-Guided AI in Vocational Informatics Education

David Immanuel Nescossa [1,*] Azhar Ahmad Smaragdina [1]

[1] Universitas Negeri Malang, Indonesia
[*] Corresponding author: David Immanuel Nescossa, Universitas Negeri Malang, Indonesia
david.immanuel.2205336@students.um.ac.id

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Abstract
Although generative Artificial Intelligence (AI) is increasingly integrated into education, experimental evidence on how Teacher-guided AI influences multidimensional student engagement in vocational secondary education remains limited. This study examined whether Teacher-guided AI functions as a pedagogical scaffold that enhances student engagement in vocational Informatics education. A quasi-experimental pretest-posttest control group design was conducted with 49 Computer and Network Engineering students. Student engagement was assessed across behavioral, emotional, cognitive, and social dimensions using a validated questionnaire, supported by classroom observations and assignment documentation. The findings revealed a moderate positive effect on overall engagement (d = 0.58). Although the adjusted ANCOVA effect was marginal, the overall pattern favored the experimental group. Cognitive engagement emerged as the most responsive dimension, suggesting that Teacher-guided AI primarily supported knowledge construction and reflective inquiry, while emotional and social engagement demonstrated weaker effects. Observation data further indicated greater participation and deeper cognitive processing among students receiving Teacher-guided AI support. These findings suggest that AI is most effective when implemented as a pedagogical scaffold rather than an answer-generation tool. The study extends multidimensional engagement theory and provides empirical evidence for structured AI integration in vocational Informatics education.

Keywords: four-dimensional engagement; quasi-experimental study; student engagement; teacher-guided ai; vocational informatics education

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INTRODUCTION
The integration of generative Artificial Intelligence (AI) in education has shifted the focus from whether to adopt AI to how to integrate it effectively without creating cognitive dependency. While tools like ChatGPT provide instant, personalized, and adaptive support (Hassan, 2026), their educational value remains conditional. Structured application deepens learning, whereas unguided use weakens it (Deng et al., 2025; Fan et al., 2025). This tension directly impacts vocational high schools, which must prepare graduates with the technical competencies and adaptability required by Industry 4.0 and Society 5.0. In this sector, AI-supported learning facilitates interactive, contextual, and industry-relevant experiences.

Within Informatics programs, where computing skills constitute a core vocational competency, this challenge manifests directly in classroom practice. A preliminary study involving 25 vocational Informatics students from separate classes indicated that 20 participants (80%) demonstrated a predominantly instrumental pattern of AI use. These students relied on AI to obtain immediate answers rather than to verify outputs, ask follow-up questions, or explore underlying concepts. This behavioral pattern highlights the lack of structured guidance regarding educational AI use, even when its use is permitted. Consequently, teacher-guided approaches are essential to promote critical and reflective student interaction with AI.

A growing body of research warns that unguided AI use erodes essential learning processes. When students accept AI outputs without evaluating accuracy, they engage less deeply and develop fewer higher-order skills, including critical reasoning and analytical thinking (Zhai et al., 2024). Experimental evidence links generative AI to cognitive dependency and reduced metacognitive regulation, where learners offload reasoning to the tool and minimize their own planning, monitoring, and evaluation (Fan et al., 2025). These passive interaction patterns occur most frequently when students lack the critical digital literacy needed to evaluate AI outputs (Hou et al., 2025).

In contrast, parallel studies demonstrate that AI benefits emerge when its application is pedagogically structured. Under teacher direction, AI provides step-by-step explanations and timely feedback, scaffolding understanding while strengthening self-regulated learning and engagement (Ng et al., 2024). Similarly, a randomized controlled trial with secondary students found that structured, strategy-focused AI support outperformed standard, unguided ChatGPT (Fütterer et al., 2026). Human AI collaboration frameworks further argue that AI is most productive when it supports, rather than replaces, student self-regulation (Järvelä et al., 2023). Collectively, these contrasting findings suggest that AI does not inherently improve learning outcomes or student engagement. Rather, its educational effectiveness depends on the pedagogical conditions under which it is implemented. Teacher guidance that encourages students to validate AI-generated outputs, ask reflective questions, and explore underlying concepts transforms AI from a potential source of cognitive dependency into a pedagogical resource that supports meaningful learning. Because Teacher-guided AI shapes students' behavioral participation, cognitive processing, emotional involvement, and social interaction, student engagement provides an appropriate multidimensional framework for evaluating these effects.

Student engagement provides an appropriate multidimensional framework for evaluating the educational effectiveness of Teacher-guided AI implementation. Conceptualize engagement through behavioral, emotional, and cognitive dimensions. Social engagement was later integrated to capture reciprocal interaction among learners and instructors (Chen et al., 2025). Recent experimental work indicates that AI can increase engagement across several of these dimensions. For instance, a quasi-experiment found that ChatGPT-based programming activities outperformed conventional methods regarding behavioral, cognitive, and emotional engagement (Lo et al., 2024), while a meta-analysis reported a moderate overall effect (Heung & Chiu, 2025). However, empirical findings remain inconsistent, and researchers frequently measure engagement as a single composite rather than analyzing each dimension independently (Lin et al., 2025; Zhai et al., 2024).

Together, these theoretical perspectives provide a coherent framework for explaining how Teacher-guided AI influences multidimensional student engagement. Constructivist theory explains the mechanism of guided AI use: learners construct knowledge through active interaction, where a more capable partner scaffolds learning within the zone of proximal development. Recent applications of the Technology Acceptance Model show that students engage with AI when they perceive it as useful and easy to use (Kim & Moon, 2025). Finally, the multidimensional engagement framework specifies the outcomes, defining the multidimensional engagement that guided, accepted AI use produces. Consequently, acceptance enables interaction, constructivist scaffolding shapes interaction quality, and engagement captures the multidimensional results.

Building upon these theoretical foundations, it becomes evident that while the conceptual links between AI utilization and engagement are clear, significant empirical gaps remain. Most existing studies focus on higher or general education rather than vocational secondary schools, and evaluate AI primarily as a technology rather than a structured pedagogical strategy. Furthermore, researchers frequently treat engagement as a single composite construct, leaving dimension-specific experimental evaluations scarce. This issue is particularly important in vocational Informatics education, where procedural and hands-on learning, authentic workplace problem-solving, and industry-based digital competencies may shape the educational role of AI differently from concept-oriented disciplines. Experimental evidence on teacher-guided AI in this context remains limited, leaving uncertainty regarding whether its effects differ across the behavioral, emotional, cognitive, and social dimensions of engagement.

This study investigates the effects of teacher-guided AI on the behavioral, emotional, cognitive, and social dimensions of student engagement among vocational Informatics students using a quasi-experimental pretest-posttest control-group design. This research measures student engagement across behavioral, emotional, cognitive, and social dimensions. The study contributes to the literature by providing experimental evidence on teacher-guided rather than autonomous AI use within an underrepresented vocational context. Furthermore, it analyzes engagement as a multidimensional construct rather than a single score. By identifying dimension-specific effects, this research reframes AI as a cognitive scaffold with varied influence across dimensions, thereby offering a robust empirical basis for the systematic pedagogical integration of AI in vocational high schools.

METHOD

This study employed a quasi-experimental pretest-posttest control group design during the second semester of the 2024/2025 academic year at a vocational high school in Gresik, Indonesia. The participants were 49 Computer and Network Engineering students, comprising 24 students in the experimental group receiving teacher-guided AI instruction and 25 students in the control group receiving conventional instruction. Purposive sampling was used because intact classes prevented random assignment. Both groups had completed the same office-application course and showed no significant pretest difference, indicating comparable baseline knowledge. The overall research procedure, from pretest through the intervention to posttest, is presented in Figure 1.

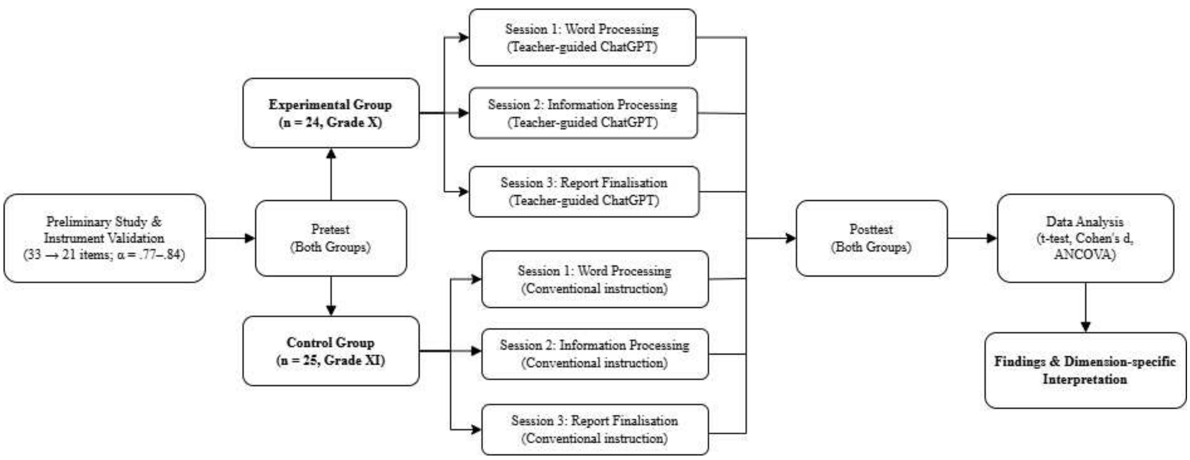

Figure 1. Flowchart of the overall research procedure

The independent variable was AI utilization as a teacher-guided learning companion, while the dependent variable was student engagement. Engagement was conceptualized across behavioral, emotional, cognitive, and social dimensions. The intervention spanned three 80-minute sessions on office applications. The experimental group utilized ChatGPT as a learning companion, whereas the control group covered identical topics through conventional methods. Rather than using AI freely, students in the experimental group applied four distinct prompting strategies detailed with example prompts in Table 1. These strategies included validating AI responses, asking follow-up questions, exploring underlying concepts, and reflecting on knowledge discrepancies. The teacher facilitated all sessions and redirected passive use. Four observation indicators monitored implementation fidelity, confirming the protocol was delivered as intended with a mean score of 3.25 on a 1-4 scale. ChatGPT was selected for its broad accessibility in secondary education (Lee et al., 2024).

Table 1. Teacher guided prompting strategies and example prompts

Prompting Strategy	Example Prompt Taught to Students
Role-based prompting	"Please act as an experienced expert in academic writing and office software. I am currently working on an assignment using Microsoft Word. Please help me create a professional document by explaining, step by step, how to use the relevant features."
Validating outputs	"Explain how to create an automatic table of contents in Microsoft Word. After setting out the steps, I will compare the results with my own method and check whether each step is correct."
Asking follow-up questions	"I've followed the steps for creating tables and formatting documents in Microsoft Word, but the results are different. Why is this happening and how can I fix it?"
Concept exploration	"As a Microsoft Office expert specialising in academic writing, explain the various ways to organise the layout of long documents in Word, such as the use of headings, tables of contents and document navigation. When is each of these features most effective?"
Reflecting on differences	"The results of my work differ from the steps you described in the third stage. I'm using the same version of Microsoft Word, but the document formatting is not the same. Please help me find the cause of this discrepancy."

Three techniques enabled data triangulation across self-reports, observed behaviors, and learning products. First, a 21-item, four-point Likert questionnaire adapted from (Fredricks et al., 2004) measured the four engagement dimensions. An initial analysis of 33 items retained 21 valid items for both classes, showing strong internal consistency with a Cronbach's alpha of 0.838 for the experimental group and 0.774 for the control group. Second, structured classroom observations utilized a 20-item checklist scored on a 1–4 scale. Third, student assignment documentation provided evidence of cognitive engagement through the assessed depth of explanations.

Data were analyzed using SPSS. After verifying normality via the Shapiro-Wilk test and variance homogeneity through Levene's test, an independent samples t-test compared posttest scores (H_0: $\mu_1 = \mu_2$; H_1: $\mu_1 > \mu_2$; $\alpha = 0.05$), with Cohen's d quantifying practical significance (Cohen, 2009). Because pretest variance violated the homogeneity assumption with a Levene's p = 0.006, an Analysis of Covariance (ANCOVA) using the pretest as a covariate was additionally applied to the composite and dimensional scores after verifying its assumptions of normality of residuals, homogeneity of variance, linearity, and homogeneity of regression slopes. Regarding ethics, the school granted institutional permission. Following established protocols for generative-AI research involving minors (Wu & Zhang, 2025), the researchers obtained informed consent and assent from students and guardians. Participation was voluntary, and all responses were anonymized.

RESULTS AND DISCUSSION

Results

The descriptive statistics indicate that both groups demonstrated comparable baseline engagement despite greater variability in the control group. An independent-samples t-test confirmed no significant pretest difference ($t = -0.385$, $p = .702$), supporting baseline equivalence before the intervention. Following the intervention, the experimental group demonstrated a substantially larger gain in engagement than the control group, providing initial evidence of a positive effect of teacher-guided AI.

Table 2. Comparison of descriptive statistics between the pretest and posttest of both groups

Group	n	M	SD	SE	Mdn	Min-Max	95% CI
Exp Pretest	24	64.21	3.26	0.66	64.0	57–72	[62.83, 65.58]
Exp Posttest	24	69.38	6.72	1.37	69.5	56–84	[66.54, 72.21]
Ctrl Pretest	25	64.72	5.68	1.14	63.0	55–77	[62.38, 67.06]
Ctrl Posttest	25	65.76	5.67	1.13	65.0	56–80	[63.42, 68.10]

Table 2 shows that both groups began with comparable engagement levels but differed noticeably after the intervention, with consistently higher posttest scores in the experimental group. Table 3 further demonstrates that the experimental group achieved a larger average gain despite individual variation, indicating stronger improvement following teacher-guided AI. The higher posttest confidence interval further supports the stability of this improvement.

Table 3. Gain scores and range

Group	Mean Gain	SD	Range
Experimental	+5.17	7.08	−7 to +19
Control	+1.04	8.93	−20 to +14

Table 4 summarizes the assumption tests required for parametric analysis. All Shapiro-Wilk tests were non-significant ($p > .05$), indicating normal score distributions. Although Levene's test revealed unequal variances at pretest, posttest variances satisfied the homogeneity assumption. Therefore, ANCOVA was employed to control for baseline differences before comparing posttest engagement.

Table 5 presents both the independent-samples t-test and ANCOVA results. After controlling for pretest scores, the experimental group maintained a higher adjusted mean than the control group, indicating that the intervention effect remained after baseline differences were statistically controlled. Although the ANCOVA result was marginally significant ($p=.053$), the moderate effect size ($\eta^2_p=.08$) suggests meaningful practical improvement.

Table 4. Results of the normality and homogeneity tests

Test	**Data**	**Result**
Shapiro-Wilk	Experimental Group Pretest : W=0,970, p=0,671	Normal
Shapiro-Wilk	Experimental Group Posttest: W=0,980, p=0,902	Normal
Shapiro-Wilk	Control Group Pretest: W=0,933, p=0,103	Normal
Shapiro-Wilk	Control Group Posttest: W=0,966, p=0,556	Normal
Levene	Pretest: F=8,144, p=0,006	Not Homogeneous
Levene	Posttest: F=0,441, p=0,510	Homogeneous

Table 5. Summary of the t-test and effect size results

Analysis	**Experimental**	**Control**	**Statistic**	**p / Effect**
Posttest t-test (M)	69.38	65.76	t(47)=2.04	p=.047, d=0.58
ANCOVA adjusted mean	69.34	65.79	F=3.95	p=.053, η^2_p=.08
ANCOVA 95% CI	[66.77, 71.91]	[63.27, 68.31]	Adj. diff=3.55	-

After adjusting for the pretest covariate, the experimental group's estimated marginal mean (69.34) remained higher than the control group's (65.79), with an adjusted difference of 3.55 closely matching the unadjusted posttest difference of 3.61. This consistency indicates that the experimental advantage was not an artifact of baseline differences. The ANCOVA effect was marginally significant (p = .053) with a moderate effect size, mirroring the significant independent-samples result (p = .047) and indicating a real but modest effect.

Table 6. Per dimension engagement analysis

Dimension	**d**	**p**	**ANCOVA p**	**Rank (ES)**	**Note**
Cognitive	0.70	.018	.024	1	Only significant; largest per-item gain
Behavioral	0.50	.084	-	2	Moderate, non-significant
Emotional	0.47	.104	-	3	Small–moderate, non-significant
Social	0.32	.267	-	4	Weakest effect

Table 6 indicates that teacher-guided AI affected the four engagement dimensions differently. Cognitive engagement demonstrated the largest and only statistically significant improvement after controlling for pretest differences, whereas behavioral and emotional engagement showed moderate but non-significant effects. Social engagement exhibited the weakest improvement, indicating that the intervention primarily strengthened cognitively demanding aspects of learning rather than all engagement dimensions equally.

Figure 2 illustrates the statistical findings by showing the intervention effects across the four engagement dimensions. The experimental group demonstrated a greater increase in overall engagement from pretest to posttest than the control group, with the largest improvement in cognitive engagement and the smallest in social engagement. This pattern was consistently supported by questionnaire data and structured classroom observations. Questionnaire results indicated a statistically significant overall improvement, with the strongest effect in the cognitive dimension, while classroom observations confirmed higher engagement across all four dimensions in the experimental group. Together, these findings indicate that teacher-guided AI produced the greatest effect on cognitive engagement, moderate effects on behavioral and emotional engagement, and the weakest effect on social engagement. The radar profile further highlights this pattern, with the experimental group's polygon extending furthest along the cognitive axis and showing the smallest separation from the control group on the social dimension.

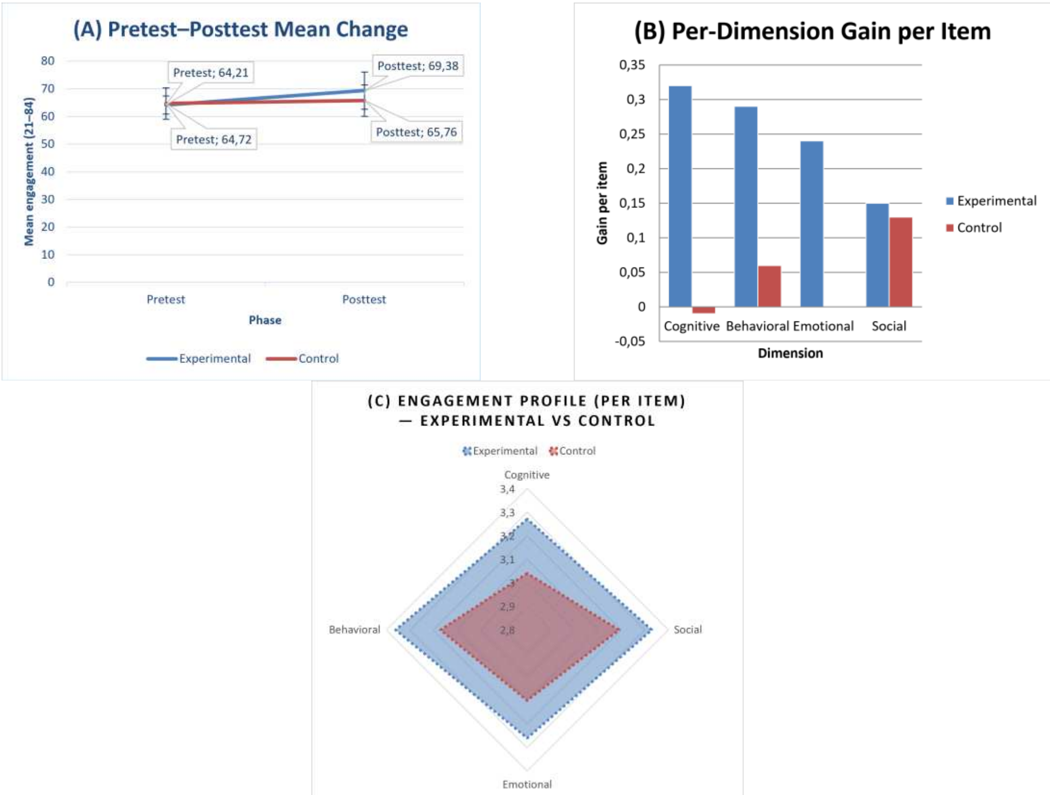

Figure 2. Engagement change by group: (A) Pretest–posttest mean change; (B) per-dimension gain per item; (C) Engagement profile experimental-control

Student assignment documentation provided complementary evidence that strengthened the questionnaire and observation findings. Students in the experimental group more frequently integrated information from multiple sources, verified AI-generated responses against learning materials, and synthesized alternative explanations before drawing conclusions. In contrast, students in the control group predominantly relied on single-source explanations and reproduced procedural steps with limited evaluation.

Discussion

The findings indicate that teacher-guided AI transformed AI from an answer provider into a cognitive scaffold that promoted active knowledge construction. By requiring students to validate AI outputs, ask follow-up questions, and explore concepts, the intervention activated metacognitive and self-regulatory processes that are often weakened during unguided AI use (Fan et al., 2025; Ng et al., 2024). Three mechanisms explain these outcomes. First, teacher scaffolding reduced cognitive dependency by requiring students to reason before consulting AI, ensuring that AI supplemented rather than replaced student thinking. Second, validating AI-generated responses against learning materials strengthened metacognitive monitoring as students evaluated accuracy, identified inconsistencies, and refined their understanding. Third, guided prompting transformed interaction from simple answer retrieval into iterative dialogue that encouraged conceptual exploration. These mechanisms explain the stronger cognitive engagement observed and reinforce that AI effectiveness depends more on pedagogical design than on technology itself (Hassan, 2026; Jose et al., 2025; Yan et al., 2025; Zhai et al., 2024). Compared with autonomous AI use, teacher-guided AI promoted evaluation, justification, and revision rather than answer-copying and metacognitive offloading, suggesting a qualitatively different engagement mechanism reflected in the stronger cognitive engagement observed in this study.

The predominance of cognitive engagement is consistent with constructivist theory, which views learning as an active process of knowledge construction. Through guided interaction, students justified solutions, evaluated responses, and explored alternatives, promoting higher-order thinking. This pattern is particularly relevant to vocational Informatics education, where procedural learning, authentic problem-solving, and technically complex tasks require adaptive support. In this context, AI functioned as scaffolding within students' zone of proximal development, supporting rather than replacing reasoning (Järvelä et al., 2023; Magwa, 2026). These findings suggest that AI is most effective when teachers actively orchestrate its pedagogical use rather than merely providing access.

Behavioral and emotional engagement improved but remained non-significant, indicating that teacher-guided AI encouraged participation, persistence, and learning interest without producing substantial between-group differences. Immediate feedback and step-by-step guidance likely reduced barriers to participation (Ng et al., 2024). This finding suggests that AI alone does not automatically promote collaborative interaction without instructional activities specifically designed for peer discussion. The engagement dimensions also appeared to be interrelated, with stronger cognitive engagement accompanying greater behavioral participation, whereas limited social gains suggest that AI functioned more effectively as an individual cognitive partner than as a collaborative learning facilitator. The marginal ANCOVA result ($p=.053$) likely reflects the modest sample size, three-session intervention, and intact-class variability, indicating limited statistical power despite a moderate practical effect. These findings suggest a possible hierarchical relationship in which cognitive engagement may provide the foundation for behavioral and, to a lesser extent, emotional engagement. Because causal relationships among engagement dimensions were not directly examined, this interpretation remains theoretical and requires verification through longitudinal or mediation-based research.

These findings extend the multidimensional engagement framework Chen et al. (2025) by showing that teacher-guided AI affects engagement dimensions differently. Unlike many higher-education studies reporting broad engagement gains, the present findings revealed a stronger effect on cognitive engagement. Unlike higher education, vocational Informatics emphasizes procedural task completion and guided problem solving, making AI prompting more directly aligned with cognitive than collaborative learning processes. Consequently, cognitive engagement improved the most because AI's step-by-step prompting directly supported reasoning and knowledge construction, whereas emotional and social engagement relied more on sustained classroom interaction and collaborative activities. The short intervention likely limited affective development because emotional engagement generally requires sustained classroom experiences beyond task completion. The study positions teacher-guided AI as instructional scaffolding whose effectiveness depends more on pedagogy than technology. It further proposes that guided prompting may foster self-regulated learning, which in turn contributes to dimension-specific engagement. Practically, the findings support structured AI integration through teacher training, responsible AI guidelines, and AI literacy development. Future research should employ longitudinal, multi-school, and randomized controlled designs while examining AI literacy and self-regulated learning as mediators, learning motivation as a moderator, and learning analytics to investigate engagement development over time.

CONCLUSION

This study positions teacher-guided AI as a pedagogical strategy rather than merely a technological tool, demonstrating that AI can function as a cognitive scaffold to enhance student engagement in vocational Informatics education. The findings show that engagement dimensions respond differently to AI-supported learning, with the strongest effect on cognitive engagement and comparatively weaker effects on emotional and social engagement. Theoretically, the study extends the multidimensional engagement framework by demonstrating the dimension-specific nature of AI-supported learning and reinforces constructivist perspectives that emphasize guided interaction as a mechanism for knowledge construction. Practically, the findings indicate that effective AI integration depends more on instructional design than on technology availability. Guidance strategies that require students to validate AI outputs, generate follow-up questions, and explore concepts critically provide a practical model for responsible AI implementation in vocational classrooms. Although limited by the single-school setting, short intervention period, and indirect assessment of technology acceptance, the study offers empirical evidence from an underexplored vocational context. Future research should validate this model through longitudinal, multi-school, and randomized studies while examining the roles of AI literacy, self-regulated learning, and collaborative learning in shaping multidimensional engagement.

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