SEMAR JOURNAL

AI as a Learning Companion: Enhancing Multidimensional Student Engagement in Vocational Informatics Education

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doi: xxx
Received: April 17th, 2025 | Revised: May 12th, 2025 | Accepted: May 18th, 2025
Available Online: May 24th, 2025 | Published Regularly: May, 2025

Abstract

The integration of Artificial Intelligence (AI) into vocational education offers opportunities to enhance student engagement through personalized, interactive, and responsive learning experiences. However, the effectiveness of AI as a learning companion in supporting multidimensional student engagement remains insufficiently explored, particularly in vocational Informatics education. This study aimed to examine the effect of AI-assisted learning on the engagement of Computer and Network Engineering (TKJ) students at SMK Umar Mas'ud Sangkapura. A quantitative quasi-experimental method employing a pretest–posttest control group design was conducted with 49 students, comprising 24 students in the experimental group and 25 in the control group. Data were collected through Likert-scale questionnaires, structured classroom observations, and learning assignment documentation. Descriptive statistics, assumption testing, an independent samples t-test, and Cohen's d analysis were employed to evaluate the intervention. The results revealed that the experimental group achieved a greater improvement in student engagement, with a mean increase of 5.17 points, compared with 1.04 points in the control group. The posttest difference was statistically significant ($t = 2.038$, $p = 0.047$), with a moderate effect size (Cohen's $d = 0.58$). Furthermore, the multidimensional findings indicated favorable engagement characteristics across behavioral, emotional, cognitive, and social dimensions, with behavioral and cognitive engagement emerging as the most prominent based on observational and learning evidence. These findings suggest that AI can serve as an effective learning companion when integrated through structured pedagogical guidance, supporting active participation, critical thinking, and meaningful learning interactions in vocational education.

Keywords: artificial intelligence; learning companion; student engagement; AI-supported learning; digital pedagogy; informatics instruction; critical digital literacy.

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Introduction

The integration of Artificial Intelligence (AI) into educational environments has expanded considerably over the past decade, fundamentally transforming instructional practices, learning interactions, and the delivery of educational content (Bond et al., 2024; Zawacki-Richter et al., 2019). Advances in AI technologies have created new opportunities for personalized instruction, adaptive learning systems, intelligent feedback mechanisms, and learner-centered educational approaches (Chen

et al., 2020; Ouyang & Jiao, 2021). These developments have become particularly relevant in vocational education, where students are expected to acquire not only theoretical knowledge but also practical competencies, technological adaptability, and problem-solving capabilities aligned with evolving industry demands. Within the context of Industry 4.0 and Society 5.0, vocational high schools (Sekolah Menengah Kejuruan or SMKs) are increasingly required to prepare graduates who can integrate technological knowledge with critical thinking, independent learning, and collaborative skills. Consequently, the pedagogically appropriate integration of AI represents an important opportunity to improve the relevance, effectiveness, and responsiveness of vocational education (Chiu et al., 2023; Crompton & Burke, 2023). Previous studies have demonstrated that AI-supported learning environments can enhance educational quality by providing personalized, interactive, and industry-oriented learning experiences that accommodate students' diverse learning needs (Yuliansah, Nugroho, & Sutirman, 2026; Yuliansah, Sholikah, & Sutirman, 2026).

In vocational high schools, Informatics constitutes a particularly important subject because it provides the technological foundations required for students to develop competencies relevant to contemporary digital industries. For students specializing in Computer and Network Engineering (Teknik Komputer dan Jaringan or TKJ), Informatics learning extends beyond the acquisition of conceptual knowledge to include analytical reasoning, technical problem-solving, computational thinking, and the practical application of digital technologies (Sun et al., 2024; Yilmaz & Karaoglan Yilmaz, 2023). These competencies require students to engage actively with instructional materials, evaluate information critically, and independently construct solutions to technical problems. However, the increasing accessibility of generative AI applications has introduced new challenges concerning how students interact with learning resources and construct their understanding (Lo, 2023; Rudolph et al., 2023). Preliminary observations conducted at SMK Umar Mas'ud Sangkapura indicated that approximately 80% of students tended to use AI primarily as a means of completing academic assignments without systematically verifying the accuracy, relevance, or validity of the generated information. This finding suggests that although AI utilization has been permitted in the instructional process, students have not received sufficient pedagogical guidance to ensure that these technologies support meaningful learning rather than merely accelerate task completion (Chan & Hu, 2023; Lim et al., 2023). Such circumstances raise concerns regarding the quality of student participation, intellectual independence, and the development of critical learning competencies.

The tendency to accept AI-generated information without adequate evaluation is consistent with broader concerns regarding students' overreliance on AI in educational settings. When students treat AI-generated responses as authoritative answers rather than informational resources that require verification, their involvement in the learning process may become superficial. This situation can reduce opportunities for independent reasoning, conceptual exploration, and reflective knowledge construction (Darvishi et al., 2024; Fan et al., 2025). Furthermore, excessive

dependence on AI-generated solutions may contribute to errors in academic tasks and undermine the development of higher-order cognitive abilities, particularly critical reasoning, analytical thinking, and independent decision-making (Gerlich, 2025; Zhai et al., 2024). In vocational education, these limitations are especially consequential because students are expected to demonstrate practical competence and the ability to address authentic technical problems. Accordingly, the educational challenge is not simply whether students use AI, but rather whether they can interact with AI critically, purposefully, and responsibly (Ng et al., 2021; Walter, 2024). Without appropriate instructional strategies, the availability of sophisticated AI applications may increase technological convenience without necessarily producing corresponding improvements in students' intellectual engagement (Bastani et al., 2025; Jose et al., 2025).

One important construct for understanding the quality of students' involvement in the learning process is student engagement. Student engagement has been widely recognized as a multidimensional construct associated with academic achievement, learning persistence, and the overall effectiveness of educational experiences (Bond et al., 2020; Wong & Liem, 2022). Fredricks et al. (2004) conceptualize student engagement as a dynamic construct influenced by contextual factors and responsive to changes in the learning environment. Their framework identifies three interrelated dimensions: behavioral, emotional, and cognitive engagement. Behavioral engagement concerns students' participation in academic activities, adherence to learning expectations, and involvement in classroom tasks. Emotional engagement refers to students' affective responses toward learning activities, including interest, enjoyment, enthusiasm, and a sense of belonging. Cognitive engagement reflects the extent to which students invest intellectual effort in understanding complex concepts, applying learning strategies, and developing deeper knowledge (Martin & Borup, 2022; Wong & Liem, 2022). Subsequent developments in engagement research have also emphasized social engagement as an additional dimension, highlighting the role of communication, interaction, and collaboration in shaping students' involvement in learning (Heilporn et al., 2021; Martin & Borup, 2022).

Method

This study employed a quantitative approach using a quasi-experimental pretest–posttest control group design to investigate the effect of artificial intelligence (AI) as a learning companion on student engagement in Informatics education. The research was conducted during the second semester of the 2024/2025 academic year at SMK Umar Mas'ud Sangkapura. A quasi-experimental design was adopted because the study involved existing classroom groups without individual random assignment, while maintaining experimental and control conditions to examine the effectiveness of the instructional intervention (Gopalan et al., 2020).

The study involved 49 students from two existing classes, comprising 24 students in the experimental group and 25 students in the control group. Participants were selected through purposive sampling based on the characteristics of the classes and the comparability of their initial learning conditions

(Campbell et al., 2020). The experimental group received Informatics instruction supported by AI as a learning companion, whereas the control group participated in conventional instruction without the structured integration of AI-based learning assistance.

Both groups completed a pretest before the instructional intervention and a posttest after its implementation. The pretest was administered to identify the initial levels of student engagement, while the posttest was used to evaluate engagement following the respective instructional approaches. The same measurement instrument was administered to both groups during the pretest and posttest stages to maintain consistency in the assessment process. The research design is illustrated in Table 1.

Table 1. Research Design of the Quasi-Experimental Study

Group	Pretest	Treatment	Posttest
Experimental Group	O1	X	O2
Control Group	O3	–	O4

a. Research Variables and Operational Definitions

This study examined two principal variables: the independent variable and the dependent variable. The independent variable was the implementation of AI as a learning companion in Informatics instruction, whereas the dependent variable was student learning engagement.

AI-assisted learning was implemented by positioning AI as a supplementary learning resource to facilitate students' understanding of instructional materials, explore alternative explanations, obtain immediate learning assistance, and develop solutions to learning-related problems (Okonkwo & Ade-Ibijola, 2021; Wollny et al., 2021). In this instructional framework, AI was intended to support students' learning activities rather than replace their independent reasoning, decision-making, or knowledge construction (Hwang et al., 2020; Kim et al., 2022).

Student engagement was conceptualized as a multidimensional construct encompassing four dimensions: behavioral, emotional, cognitive, and social engagement. The measurement framework was based on the conceptualization of student engagement proposed by Fredricks et al. (2004), extended to incorporate the social dimension to capture interpersonal interactions and collaborative participation during the learning process.

The four dimensions were operationally defined as follows:

1. Behavioral engagement referred to students' active participation in classroom activities, attentiveness, involvement in instructional tasks, and consistency in completing assigned learning activities.
2. Emotional engagement represented students' affective responses to the learning process, including interest, enthusiasm, enjoyment, and positive attitudes toward Informatics instruction.
3. Cognitive engagement concerned students' intellectual investment in learning activities, including critical thinking, information evaluation, problem-solving, and the application of appropriate learning strategies.

4. Social engagement referred to students' involvement in interpersonal learning interactions, including communication, collaborative problem-solving, sharing ideas, and interaction with teachers and peers.

These four dimensions provided a comprehensive framework for examining students' participation, emotional involvement, intellectual investment, and social interaction throughout the instructional process (Fredricks et al., 2004).

b. Data Collection Techniques and Research Instruments

Data were collected using three complementary techniques: structured questionnaires, classroom observations, and learning assignment documentation. These techniques were employed to obtain quantitative measurements and supplementary evidence concerning students' engagement throughout the instructional process.

First, a structured questionnaire using a Likert-scale response format was administered to all participants during the pretest and posttest stages. The instrument was developed based on the student engagement indicators proposed by Fredricks et al. (2004), encompassing behavioral, emotional, cognitive, and social engagement. The same questionnaire was administered to both groups before and after the intervention to maintain consistency in the measurement process.

Prior to its implementation, the questionnaire underwent expert validation to assess the relevance, clarity, and suitability of its items in relation to the research constructs. Instrument reliability was evaluated using Cronbach's Alpha to examine the internal consistency of the questionnaire. These procedures were intended to ensure that the instrument adequately represented the dimensions of student engagement and provided consistent measurements.

Second, structured classroom observations were conducted throughout the instructional intervention to document students' engagement in authentic learning situations. The observations focused primarily on behavioral and social engagement, including classroom participation, attentiveness, involvement in learning activities, communication, and collaboration with teachers and peers. Predetermined observation indicators were used to maintain consistency in documenting students' classroom behaviors.

Third, learning assignment documentation was collected to provide supplementary evidence of students' cognitive engagement. The documented learning products were examined in relation to students' involvement in completing assignments, their approaches to problem-solving, and their ability to process and apply information obtained during learning activities. Particular attention was given to students' ability to examine AI-generated information, evaluate its accuracy and relevance, and incorporate appropriate information into their learning tasks.

The questionnaire data constituted the primary source for quantitative statistical analysis, while classroom observations and assignment documentation provided complementary evidence to support the interpretation of student engagement.

c. Data Analysis Techniques

The collected data were analyzed using descriptive and inferential statistical procedures. Descriptive statistics were employed to summarize the characteristics of student engagement scores, whereas inferential statistics were used to examine differences between the experimental and control groups following the instructional intervention. All statistical hypothesis tests were evaluated at a significance level of 0.05.

1. Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to summarize the pretest and posttest scores of both research groups. The statistical indicators included the mean, standard deviation (SD), minimum score, and maximum score. The mean represented the average student engagement score, while the standard deviation indicated the variability of scores within each group. Minimum and maximum values were used to describe the range of observed scores.

Additionally, changes in student engagement were initially examined by calculating the difference between the mean pretest and posttest scores for each group. This comparison provided an overview of the improvement observed following the respective instructional approaches. The descriptive statistical results for the experimental and control groups are presented in Table 2.

Table 2. Descriptive Statistics of Pretest and Posttest Scores

Group	Test	n	Mean	SD	Min	Max	Mean Change (Δ)
Experimental	Pretest	24	64.21	3.26	57	72	–
Experimental	Posttest	24	69.38	6.72	56	84	+5.17
Control	Pretest	25	64.72	5.68	55	77	–
Control	Posttest	25	65.76	5.67	56	80	+1.04

2. Assumption Testing

Before conducting the primary inferential analysis, normality and homogeneity tests were performed to evaluate the assumptions underlying the independent samples t-test.

Data normality was examined using the Shapiro–Wilk test because the sample size in each group was fewer than 50 participants (Mishra et al., 2019). The test was conducted separately for the pretest and posttest scores of both groups. A significance value greater than 0.05 (p greater than 0.05) indicated that the normality assumption was not violated.

As presented in Table 3, the experimental group's pretest and posttest scores produced significance values of 0.671 and 0.902, respectively. Meanwhile, the control group's pretest and posttest scores yielded significance values of 0.103 and 0.556, respectively. All significance values exceeded the 0.05 threshold, indicating that the four datasets satisfied the normality assumption.

Table 3. Results of the Shapiro–Wilk Normality Test

Data	Shapiro–Wilk (W)	Sig. (p)	Description
Experimental Group Pretest	0.970	0.671	Normal
Experimental Group Posttest	0.980	0.902	Normal
Control Group Pretest	0.933	0.103	Normal
Control Group Posttest	0.966	0.556	Normal

The homogeneity of variance assumption was examined using Levene's test to determine whether the score variances between the experimental and control groups were statistically comparable. The pretest results indicated unequal variances (F = 8.144, p = 0.006), whereas the posttest results demonstrated homogeneous variances (F = 0.441, p = 0.510).

Since the posttest significance value exceeded 0.05, the equal variance assumption was considered satisfied for the comparison of posttest scores. Consequently, the equal-variances-assumed results of the independent samples t-test were used for the primary between-group analysis.

3. Independent Samples t-Test

An independent samples t-test was performed to determine whether a statistically significant difference existed between the posttest engagement scores of the experimental and control groups. This test was selected because the groups consisted of different participants, and the posttest data satisfied the assumptions of normality and homogeneity of variance (Kim & Park, 2019).

The hypotheses were formulated as follows:

a) H_0 : There is no statistically significant difference in the mean student engagement scores between the experimental and control groups after the instructional intervention ($\mu_1 = \mu_2$).

b) H_1 : There is a statistically significant difference in the mean student engagement scores between the experimental and control groups after the instructional intervention ($\mu_1 \neq \mu_2$).

The significance level was established at 0.05. The null hypothesis was rejected when the two-tailed significance value was below 0.05 ($p < 0.05$). Conversely, when the significance value was equal to or greater than 0.05, the null hypothesis was not rejected.

The analysis focused on comparing the posttest scores to determine whether students who received AI-assisted instruction demonstrated significantly different engagement levels from those who participated in conventional instruction. The t-statistic, degrees of freedom, significance value, and 95% confidence interval of the mean difference were examined to evaluate the statistical evidence. The results of the independent-samples t-test are presented in Table 4.

Table 4. Results of the Independent Samples t-Test (Posttest)

Assumption	t	df	Sig. (2-tailed)	95% CI of the Mean Difference
Equal variances assumed	2.038	47	0.047	0.047–7.183
Equal variances not assumed	2.031	45.046	0.048	0.031–7.199

4. Effect Size Analysis

In addition to statistical significance testing, Cohen's d was calculated to estimate the magnitude of the difference in posttest engagement scores between the experimental and control groups. Effect size analysis was incorporated to provide an indication of the practical magnitude of the observed difference beyond the statistical significance of the hypothesis test.

Cohen's d was calculated using the following formula:

$$d = \frac{X_1 - X_2}{XD_{pooled}}$$

The pooled standard deviation was calculated using the following equation:

$$SD_{pooled} = \sqrt{\frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}}$$

Where:

- X_1 represents the mean posttest score of the experimental group;
- X_2 represents the mean posttest score of the control group;
- SD_{pooled} represents the pooled standard deviation;
- n_1 and n_2 represent the sample sizes of the experimental and control groups, respectively; and
- SD_1 and SD_2 represent the corresponding posttest standard deviations.

Based on the descriptive statistical results, the experimental group obtained a mean posttest score of 69.38, while the control group obtained a mean of 65.76. The pooled standard deviation was 6.206. Therefore, Cohen's d was calculated as follows:

$$d = \frac{69.38 - 65.76}{6.206} = 0.58$$

The resulting effect size was interpreted using conventional benchmarks, in which values of approximately 0.20, 0.50, and 0.80 indicate small, moderate, and large effects, respectively (Cohen, 1988; Kraft, 2020). Accordingly, the obtained Cohen's d of 0.58 represented a moderate effect, suggesting that AI-assisted learning was associated with a meaningful difference in student engagement between the experimental and control groups. The results of the effect size analysis are presented in Table 5.

Table 5. Results of the Cohen's d Effect Size Analysis

Component	Value
Experimental Group Mean (Posttest)	69.38
Control Group Mean (Posttest)	65.76
Pooled Standard Deviation	6.206
Cohen's d	0.58
Effect Size Category	Moderate Effect (0.50 ≤ d < 0.80)

Results and Discussion

This section presents the findings of the study and provides a comprehensive discussion of the effectiveness of Artificial Intelligence (AI) as a learning companion in Informatics education. The analysis focuses on how AI-assisted instruction influences the learning engagement of Computer and Network Engineering (TKJ) students, supported by descriptive and inferential statistical results as well as observations of students' learning activities. To establish a systematic and comprehensive discussion, the findings are organized into three main aspects. First, a comparative analysis of student learning engagement before and after AI-assisted instruction is presented to examine changes in students' engagement across the experimental and control groups. Second, the effectiveness of AI as a learning companion is evaluated through statistical significance testing and effect size analysis to determine the magnitude of its influence. Third, the discussion examines the multidimensional characteristics of student engagement, encompassing behavioral, emotional, cognitive, and social dimensions, to provide deeper insights into how AI-supported learning contributes to students' participation, motivation, critical thinking, and social interaction. These three aspects collectively provide an empirical and pedagogical understanding of the role of AI in fostering meaningful learning engagement within vocational education.

a. Comparative Analysis of Student Learning Engagement Before and After AI-Assisted Instruction

The comparative analysis of student learning engagement was conducted to examine the changes in students' engagement before and after the instructional intervention in both the experimental and control groups. The comparison focused on the mean scores, standard deviations, and score distributions obtained during the pretest and posttest assessments. These measurements provided an initial understanding of the students' engagement conditions and the extent to which the two instructional approaches contributed to changes in their learning experiences.

Before the intervention, the experimental group consisted of 24 students with a mean pretest score of 64.21 and a standard deviation of 3.26. Meanwhile, the control group consisted of 25 students with a mean pretest score of 64.72 and a standard deviation of 5.68. The difference between the two group means was only 0.51 points, indicating that their initial average engagement scores were relatively close. However, the difference in standard deviations suggests that the distribution of engagement scores was more varied in the control group than in the experimental group. These findings provide an important descriptive baseline for interpreting the subsequent changes in student engagement, although the similarity of the means alone does not establish statistical equivalence between the groups (Gopalan et al., 2020).

Table 6. Comparative Descriptive Statistics of Student Learning Engagement at the Pretest Stage

Indicator	Experimental Group	Control Group	Mean Difference
Number of Students (n)	24	25	–
Mean Score	64.21	64.72	-0.51
Standard Deviation	3.26	5.68	-2.42
Minimum Score	57	55	+2.00
Maximum Score	72	77	-5.00
Score Range	15	22	-7.00

The descriptive statistics in Table 6 indicate that both groups started the study with relatively similar average levels of student engagement. Nevertheless, the control group exhibited greater score variability, as reflected in its higher standard deviation and wider score range. This suggests that students in the control group had more heterogeneous initial engagement levels. Such variation is relevant when interpreting the posttest findings because differences in the distribution of scores may influence the observed patterns of improvement. Therefore, the baseline comparison should be interpreted as evidence of similarity in average scores rather than proof of complete equivalence between the groups. This distinction is particularly important in quasi-experimental research, where participants are selected from existing classes rather than randomly assigned (Gopalan et al., 2020).

Following the instructional intervention, the experimental group demonstrated a more substantial increase in student engagement than the control group. The experimental group's mean score increased from 64.21 to 69.38, whereas the control group's mean increased from 64.72 to 65.76. These findings suggest that students who participated in AI-assisted Informatics learning experienced a greater improvement in their overall engagement scores than those who received conventional instruction.

Table 7. Comparative Descriptive Statistics of Student Learning Engagement at the Posttest Stage

Indicator	Experimental Group	Control Group	Mean Difference
Number of Students (n)	24	25	–
Mean Score	69.38	65.76	+3.62
Standard Deviation	6.72	5.67	+1.05
Minimum Score	56	56	0.00
Maximum Score	84	80	+4.00
Score Range	28	24	+4.00

As presented in Table 7, the experimental group achieved a posttest mean score of 69.38, which was 3.62 points higher than the control group's mean score of 65.76. This difference indicates a more favorable descriptive outcome for students receiving AI-assisted instruction. Furthermore, the experimental group recorded a higher maximum score of 84, compared with 80 in the control group, although both groups had the same minimum score of 56. The larger posttest standard deviation in the experimental group also indicates greater variability in the final scores. This suggests that the improvement was not necessarily uniform across all students,

highlighting the importance of considering individual differences when evaluating the effectiveness of AI-supported learning.

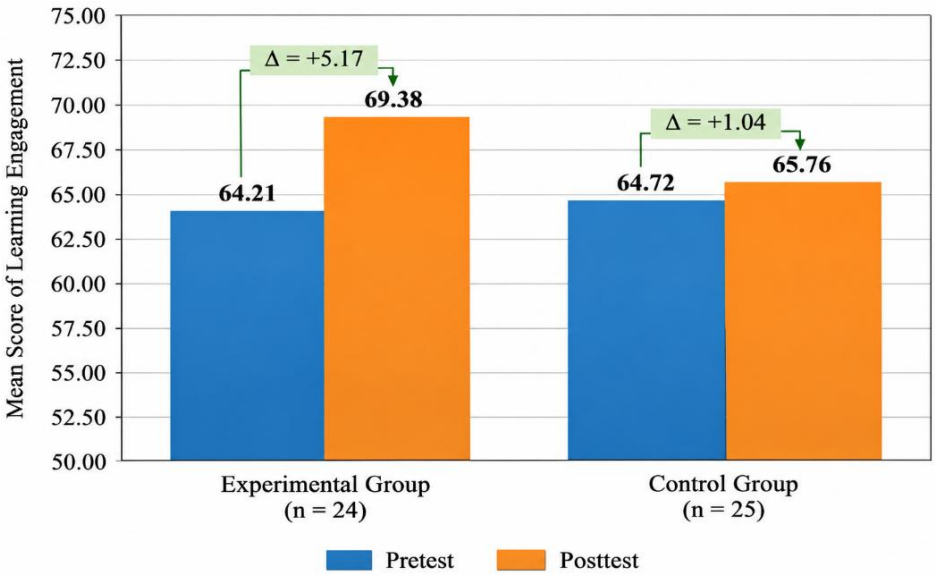

Figure 1. Comparison of Mean Pretest and Posttest Student Learning Engagement Scores between the Experimental and Control Groups

To further clarify the magnitude of these changes, the mean score differences between the pretest and posttest were examined for each group. The experimental group experienced an increase of 5.17 points, while the control group showed an increase of only 1.04 points. Thus, the difference in descriptive improvement between the two groups reached 4.13 points. This comparison provides an indication that the improvement observed in the experimental group was considerably greater than that in the control group.

Table 8. Comparison of Mean Score Improvements between the Experimental and Control Groups

Indicator	Experimental Group	Control Group	Difference
Pretest Mean	64.21	64.72	-0.51
Posttest Mean	69.38	65.76	+3.62
Mean Improvement	+5.17	+1.04	+4.13
Pretest SD	3.26	5.68	-2.42
Posttest SD	6.72	5.67	+1.05
Improvement Relative to Initial Mean (%)	8.05	1.61	+6.44 percentage points

The results in Table 8 provide a clearer representation of the differences in learning engagement improvements between the two instructional groups. The experimental group demonstrated an increase of 5.17 points, equivalent to approximately 8.05% of its initial mean score. In comparison, the control group experienced an increase of only 1.04 points, or approximately 1.61% of its initial mean score. The resulting difference in improvement was

4.13 points, suggesting that the AI-assisted instructional approach was associated with a more substantial descriptive improvement in student engagement. Nevertheless, these percentages represent relative changes in group mean scores and should not be interpreted as independent measures of statistical significance.

The greater improvement observed in the experimental group can be interpreted through the pedagogical role of AI as an interactive learning companion. Unlike conventional instructional approaches that may rely predominantly on teacher-directed explanations, AI-supported learning provides opportunities for students to explore concepts, ask questions, receive immediate responses, and obtain alternative explanations according to their learning needs. These interactions may encourage students to become more actively involved in the instructional process while providing additional opportunities to understand complex Informatics concepts. In vocational education, where students are expected to develop practical competencies and solve technical problems, such instructional support can contribute to a more responsive and engaging learning environment. Previous research has similarly indicated that AI-oriented instructional strategies can enhance student engagement and learning outcomes when integrated into appropriately designed learning activities (Deng et al., 2025; Deng & Yu, 2023).

Furthermore, the findings can be understood through the constructivist perspective, which emphasizes the active construction of knowledge through interaction with the learning environment. In this context, AI can function as a form of instructional support by providing explanations, feedback, and opportunities for further exploration. When students are encouraged to examine AI-generated responses, formulate follow-up questions, and verify the information obtained, their learning activities can extend beyond simply receiving information. This approach may facilitate deeper involvement in the learning process and strengthen students' responsibility for constructing their own understanding. Previous research has also emphasized the importance of structured pedagogical guidance in integrating AI into vocational education to improve the quality of learning interactions (Chang et al., 2023; Yuliansah, Sholikah, & Sutirman, 2026).

Overall, the comparative findings demonstrate that the experimental group achieved a greater descriptive improvement in student learning engagement than the control group. The difference between the mean score increases suggests that integrating AI as a learning companion may provide additional instructional benefits beyond those observed in conventional learning. However, these descriptive findings alone cannot establish a statistically significant treatment effect or demonstrate that AI was the sole cause of the improvement (Gopalan et al., 2020). The inferential statistical results are therefore necessary to determine whether the observed posttest difference is statistically significant. These findings provide the foundation for the subsequent analysis of the effectiveness of AI as a learning companion through statistical significance testing and effect size estimation.

b. The Effectiveness of AI as a Learning Companion: Statistical Significance and Effect Size

The effectiveness of Artificial Intelligence (AI) as a learning companion in Informatics education was further examined through inferential statistical analysis and effect size estimation. While the descriptive findings demonstrated a greater improvement in student engagement in the experimental group, inferential analysis was necessary to determine whether the observed difference between the experimental and control groups was statistically significant. Accordingly, the analysis involved examining the assumptions of normality and homogeneity of variance, conducting an independent samples t-test, and calculating Cohen's d to evaluate the magnitude of the observed difference.

Before hypothesis testing, the normality of the pretest and posttest scores was assessed using the Shapiro–Wilk test. This procedure was appropriate for the present study because each group consisted of fewer than 50 participants. The results indicated that all four datasets satisfied the normality assumption, with significance values exceeding 0.05. Specifically, the experimental group's pretest and posttest scores produced p-values of 0.671 and 0.902, respectively, while the corresponding values for the control group were 0.103 and 0.556. These findings indicate that there was insufficient statistical evidence to reject the normality assumption for any of the four datasets.

Table 9. Results of Normality and Homogeneity Assumption Tests

Statistical Test	Dataset	Test Statistic	p-value	Decision
Shapiro–Wilk	Experimental Pretest	W = 0.970	0.671	Normal
Shapiro–Wilk	Experimental Posttest	W = 0.980	0.902	Normal
Shapiro–Wilk	Control Pretest	W = 0.933	0.103	Normal
Shapiro–Wilk	Control Posttest	W = 0.966	0.556	Normal
Levene's Test	Pretest	F = 8.144	0.006	Not homogeneous
Levene's Test	Posttest	F = 0.441	0.510	Homogeneous

The results presented in Table 9 demonstrate that the normality assumption was satisfied for both assessment periods and both research groups. However, the homogeneity test revealed different findings between the pretest and posttest measurements. The pretest data demonstrated unequal variances ($F = 8.144$, $p = 0.006$), whereas the posttest data satisfied the homogeneity assumption ($F = 0.441$, $p = 0.510$). This distinction is important because similarity in mean scores does not necessarily indicate similarity in score distributions. The unequal pretest variances suggest that the initial engagement scores exhibited different levels of variability between the two classes. Nevertheless, the posttest homogeneity result supported the use of the equal-variances-assumed procedure for the primary comparison of posttest scores.

Following the assumption tests, an independent samples t-test was conducted to examine the difference in posttest student engagement between the experimental and control groups. The analysis produced a t-statistic of 2.038 with 47 degrees of freedom and a two-tailed significance value of 0.047.

Since the significance value was below the predetermined threshold of 0.05, the null hypothesis was rejected. This result indicates a statistically significant difference in student engagement between the two groups following the instructional intervention.

The experimental group achieved a posttest mean score of 69.38, compared with 65.76 in the control group, resulting in a mean difference of 3.62 points. Furthermore, the 95% confidence interval ranged from 0.047 to 7.183. Because the entire interval was above zero, the result provides additional evidence that the experimental group achieved higher engagement scores than the control group. The statistical comparison is summarized in Table 10.

Table 10. Results of the Independent Samples t-Test and Confidence Interval Analysis

Statistical Component	Experimental Group	Control Group	Test Result
Sample Size (n)	24	25	49
Posttest Mean	69.38	65.76	Difference = 3.62
Posttest Standard Deviation	6.72	5.67	–
t-statistic	–	–	2.038
Degrees of Freedom (df)	–	–	47
Significance (2-tailed)	–	–	0.047
95% Confidence Interval	–	–	0.047–7.183
Statistical Decision	–	–	Significant

The findings in Table 10 provide statistical support for the effectiveness of AI-assisted instruction in improving student engagement relative to conventional learning. The positive mean difference of 3.62 points indicates that students in the experimental group achieved higher engagement scores after the intervention. Moreover, the lower and upper boundaries of the 95% confidence interval (0.047 and 7.183, respectively) indicate that the estimated difference remained positive within the reported confidence interval. Although the result is statistically significant, the p-value of 0.047 is relatively close to the 0.05 threshold. Therefore, the finding should be interpreted with appropriate caution rather than as evidence of an overwhelmingly strong effect. Nevertheless, the result is consistent with previous research indicating that generative AI can improve student engagement when its implementation is supported by structured pedagogical strategies (Heung & Chiu, 2025; Lo et al., 2024). Similarly, Zheng et al. (2023) reported a large effect of AI applications on learning achievement, and Wu and Yu (2024) found that AI chatbots had a large effect on students' learning outcomes. Previous findings have also identified a positive contribution of ChatGPT utilization to students' learning motivation in programming courses (Yilmaz & Karaoglan Yilmaz, 2023), while emphasizing the continuing importance of teacher support in sustaining students' motivation to learn with AI (Chiu et al., 2024).

To complement the hypothesis testing, Cohen's d was calculated to determine the magnitude of the difference between the two groups. This analysis is important because statistical significance does not necessarily indicate that an observed difference has substantial practical implications. Based on the posttest means of 69.38 and 65.76 and a pooled standard deviation of 6.206, the calculated

Cohen's d was 0.58. According to the conventional interpretation proposed by Cohen (1988), an effect size of approximately 0.50 represents a moderate effect, whereas values around 0.20 and 0.80 represent small and large effects, respectively.

Table 11. Summary of Effect Size Estimation Using Cohen's d

Component	Experimental Group	Control Group	Overall Result
Sample Size	24	25	49
Posttest Mean	69.38	65.76	Mean Difference = 3.62
Posttest Standard Deviation	6.72	5.67	–
Pooled Standard Deviation	–	–	6.206
Cohen's d	–	–	0.58
Effect Size Classification	–	–	Moderate
Interpretation	–	–	Meaningful standardized difference

As demonstrated in Table 11, the Cohen's d coefficient of 0.58 falls within the moderate effect category, indicating that the difference in student engagement between the experimental and control groups was not merely statistically detectable but also meaningful in terms of standardized magnitude. This finding suggests that the integration of AI as a learning companion provided an observable advantage in student engagement under the instructional conditions examined in this study. However, the moderate effect should not be interpreted as a 58% increase in student engagement, because Cohen's d represents a standardized mean difference rather than a percentage improvement (Funder & Ozer, 2019; Kraft, 2020). The result also indicates that AI integration does not produce identical outcomes for every student, as individual engagement levels may remain influenced by prior knowledge, learning preferences, digital literacy, and the quality of instructional facilitation.

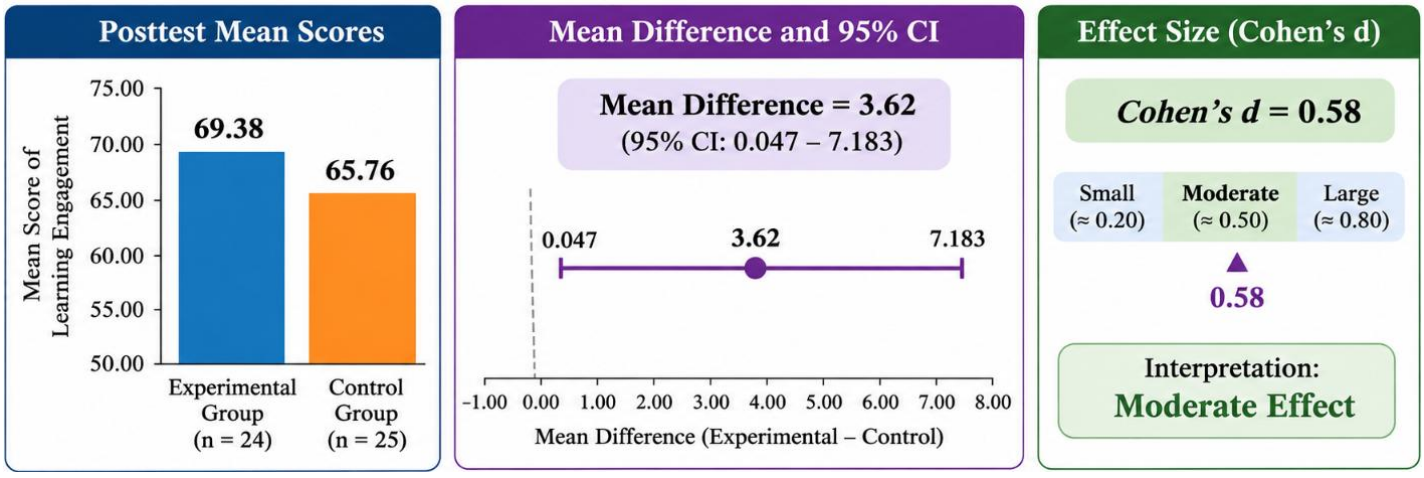

Figure 2. Statistical Evidence of the Effectiveness of AI as a Learning Companion Based on Mean Difference, 95% Confidence Interval, and Cohen's d

The statistical findings collectively suggest that the integration of AI as a learning companion can provide meaningful instructional support for improving student engagement in vocational Informatics education. One possible explanation concerns the interactive characteristics of AI, which allow students to obtain immediate explanations, explore alternative approaches to solving problems, and revisit concepts that they have not fully understood (Chang et al., 2023; Kuhail et al., 2023). These opportunities may encourage students to become more actively involved in learning activities rather than relying exclusively on teacher-directed explanations. However, the educational benefits of AI depend substantially on how the technology is integrated into instructional activities. Students need to be encouraged to evaluate generated information, formulate follow-up questions, and construct their own understanding rather than passively accepting AI-generated answers.

This interpretation is consistent with the findings of Hou et al. (2025), who emphasized the importance of critical thinking in shaping students' reliance behaviors when using generative AI for problem-solving. Their findings highlight that students' interaction with AI should involve reflective evaluation rather than uncritical acceptance of generated information. In the present study, the use of AI as a learning companion is therefore understood not simply as providing technological assistance, but as creating opportunities for students to engage more purposefully with learning materials. Teacher facilitation remains essential to ensure that AI-supported activities promote independent reasoning, critical evaluation, and meaningful participation. This consideration is also consistent with previous findings concerning the role of teacher guidance in optimizing the educational benefits of AI utilization among secondary school students (Celik et al., 2022; Chiu et al., 2024).

From a broader pedagogical perspective, the moderate effect size observed in this study indicates that AI-assisted learning represents a promising instructional approach, although it should not be regarded as a standalone solution to all challenges associated with student engagement. Learning engagement is influenced by multiple interacting factors, including instructional design, classroom interactions, student characteristics, and the learning environment. Consequently, the effectiveness of AI integration should be understood within the specific instructional context in which it is implemented. Previous research has similarly emphasized that the contribution of AI to student engagement and academic performance depends on the quality of instructional design and the pedagogical strategies accompanying its implementation (Deng et al., 2025; Lo et al., 2024).

Overall, the combination of inferential statistical testing and effect size analysis provides evidence supporting the positive contribution of AI as a learning companion to student engagement in Informatics education. The significant difference in posttest scores ($p = 0.047$), together with the moderate effect size (Cohen's $d = 0.58$), indicates that the experimental group achieved more favorable engagement outcomes than the control group. These findings strengthen the argument that AI can function as a meaningful instructional companion when integrated through structured and pedagogically guided learning activities.

Nevertheless, given the quasi-experimental design and the unequal pretest variances, the findings should be interpreted within the limitations of the study rather than as definitive proof of a universal causal effect (Gopalan et al., 2020). The results provide an empirical foundation for examining more specifically how AI-supported instruction contributes to behavioral, emotional, cognitive, and social engagement, which is discussed in the following subsection.

c. Multidimensional Analysis of Student Engagement in AI-Assisted Informatics Learning

Student engagement is a multidimensional construct that extends beyond students' participation in classroom activities. It encompasses behavioral, emotional, cognitive, and social aspects that collectively shape the quality of students' involvement in the learning process. In this study, the implementation of Artificial Intelligence (AI) as a learning companion was examined in relation to these four dimensions to provide a more comprehensive understanding of how AI-assisted Informatics instruction influenced students' learning experiences. The findings were derived from questionnaire responses, structured classroom observations, and assignment documentation collected during the instructional intervention. Overall, the experimental group demonstrated favorable engagement characteristics across all four dimensions, although the nature and observable manifestations of these improvements differed across dimensions.

1. Behavioral and Emotional Engagement

Behavioral engagement represents students' active participation in academic activities, including attentiveness, task completion, classroom participation, and involvement in instructional processes. Observational findings during the intervention indicated that students in the experimental group demonstrated more active learning behaviors than those in the control group. Specifically, students became more involved in taking notes, completing assignments independently, and asking questions during classroom activities. In contrast, students in the control group continued to demonstrate relatively passive participation. These observations suggest that the integration of AI as a learning companion provided additional opportunities for students to engage directly with instructional materials and participate more actively in learning activities.

Table 12. Observed Behavioral Engagement in AI-Assisted Informatics Learning

Behavioral Indicator	Experimental Group	Control Group	Observed Evidence
Classroom participation	More active involvement	Relatively passive participation	Increased participation during lessons
Note-taking activities	More consistent	Less actively demonstrated	Students recorded explanations and important information
Assignment completion	More independent involvement	Conventional task completion	Students actively used AI to support task completion
Questioning behavior	More frequent questions	Less frequent questioning	Students requested additional explanations

Behavioral Indicator	Experimental Group	Control Group	Observed Evidence
Learning task involvement	Greater interaction with materials	More limited interaction	Students explored instructional content more actively

The findings presented in Table 12 indicate that the experimental group exhibited more favorable behavioral engagement characteristics, particularly in classroom participation, independent task completion, and questioning activities. These behaviors suggest that AI-supported learning may encourage students to take a more active role in their learning process rather than relying exclusively on teacher explanations. One possible explanation is that AI provides immediate responses and alternative explanations, allowing students to explore instructional materials according to their individual learning needs. This interpretation is consistent with Lo et al. (2024), whose review found robust evidence of behavioral engagement in ChatGPT-supported learning, and with Ng et al. (2024), who reported that a guided generative AI chatbot enhanced secondary students' behavioral engagement and motivation. Furthermore, these findings align with Fredricks et al. (2004), who conceptualized behavioral engagement as students' positive participation in academic and classroom activities.

In addition to behavioral engagement, the emotional dimension also demonstrated favorable characteristics in the experimental group. Emotional engagement concerns students' affective responses to the learning environment, including interest, enthusiasm, enjoyment, and perceived learning comfort. The posttest questionnaire indicated higher scores for the experimental group on items related to learning interest, enthusiasm, and comfort. This suggests that the integration of AI may have contributed to a more responsive and interactive learning experience, potentially reducing difficulties encountered by students when dealing with technical and abstract Informatics concepts (Hmoud et al., 2025; Septiyanti et al., 2024).

Table 13. Characteristics of Emotional Engagement in AI-Assisted Informatics Learning

Emotional Indicator	Experimental Group	Control Group	Pedagogical Interpretation
Learning interest	Higher posttest responses	Relatively conventional learning experience	AI may stimulate curiosity toward Informatics concepts
Learning enthusiasm	More favorable responses	Less interactive learning experience	Immediate feedback may support learning motivation
Learning comfort	More favorable responses	More dependent on conventional explanations	Alternative explanations may reduce learning difficulties
Positive learning attitudes	More favorable emotional responses	Conventional classroom interaction	Responsive learning support may improve perceptions of learning
Learning motivation	Greater motivational engagement	Relatively limited instructional variation	Personalized assistance may encourage continued participation

As illustrated in Table 13, the emotional engagement findings suggest that AI-assisted learning created a more supportive instructional environment in which students could obtain

explanations and learning assistance according to their needs. This characteristic is particularly relevant in vocational Informatics education, where technical concepts may require repeated explanations and practical examples to achieve meaningful understanding. The availability of AI-based assistance may help students overcome initial learning difficulties, thereby supporting more positive emotional responses toward instructional activities. These findings are consistent with Ng et al. (2024), who found that ChatGPT-enhanced instruction reduced secondary students' learning anxiety while promoting their motivation, and with Heung and Chiu (2025), who reported a medium effect of ChatGPT-based learning on emotional engagement. Nevertheless, the observed emotional benefits should be interpreted as characteristics of the experimental group's responses rather than evidence of independently quantified causal effects for each emotional indicator.

2. Cognitive and Social Engagement

Cognitive engagement represents the extent to which students invest intellectual effort in understanding instructional materials, evaluating information, applying learning strategies, and solving problems. In this study, cognitive engagement was examined primarily through the documentation of students' learning assignments and the quality of their learning products. The findings indicated that students in the experimental group produced more elaborated responses, supported by deeper explanations and more comprehensive justifications than those in the control group. This difference suggests that AI-assisted instruction provided opportunities for students to move beyond obtaining immediate answers toward exploring concepts, examining alternative solutions, and developing a more thorough understanding of Informatics materials (Essel et al., 2024).

An important characteristic of this finding is the role of AI in supporting students' reflective learning processes. Rather than treating AI-generated responses as final answers, students were encouraged to use the information as a starting point for further examination and validation. This approach is particularly important because the educational value of generative AI depends not only on the availability of information but also on students' ability to evaluate and apply that information critically (Walter, 2024). Hou et al. (2025) demonstrated the importance of reflective AI utilization in supporting deeper cognitive processing. Similarly, Zhai et al. (2024) emphasized that unguided AI use may undermine students' cognitive development, whereas appropriate instructional scaffolding can encourage more meaningful intellectual engagement.

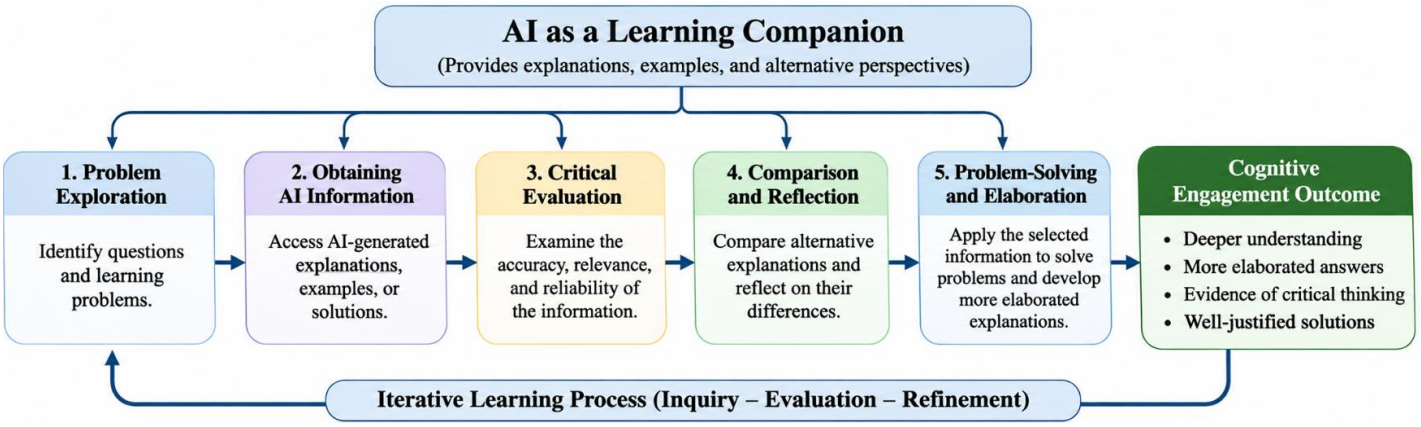

Figure 3. Cognitive Engagement in AI-Assisted Informatics Learning: From AI-Generated Information to Critical Evaluation and Problem-Solving

The cognitive engagement findings are further summarized in Table 14, which presents the observable differences in students' intellectual involvement during the instructional process.

Table 14. Comparative Characteristics of Cognitive and Social Engagement in AI-Assisted Informatics Learning

Dimension	Indicator	Experimental Group	Observed Evidence
Cognitive	Information processing	More elaborated responses	More comprehensive assignment explanations
Cognitive	Critical evaluation	Greater emphasis on validation	Examination of AI-generated information
Cognitive	Problem-solving	More developed justifications	Students explored alternative solutions
Cognitive	Conceptual understanding	More detailed explanations	Learning products demonstrated deeper elaboration
Social	Peer interaction	More active discussions	Students compared AI-generated responses
Social	Collaborative learning	More opportunities for discussion	Students exchanged ideas and interpretations
Social	Knowledge sharing	More frequent discussion of alternative answers	Students discussed differences in AI responses
Social	Classroom communication	More productive interactions	AI-generated information became a discussion stimulus

The findings in Table 14 indicate that cognitive engagement was reflected in the quality of students' learning products, particularly in the elaboration of explanations, the provision of justifications, and the examination of AI-generated information. These characteristics suggest that AI-assisted learning can provide opportunities for students to engage in deeper intellectual activities when its use is accompanied by critical evaluation and appropriate instructional guidance. Rather than simply reproducing generated answers, students in the experimental group demonstrated greater involvement in processing and explaining the information obtained. This finding reinforces the argument that AI should function as an intellectual support mechanism that encourages students to develop their own understanding.

The findings are consistent with Hou et al. (2025) and Zhai et al. (2024), who highlighted the importance of reflective AI utilization and critical instructional scaffolding in supporting students' cognitive development.

In contrast to cognitive engagement, social engagement demonstrated a comparatively less pronounced improvement, a pattern that mirrors the limited evidence on social interaction in ChatGPT-supported learning (Lo et al., 2024). Nevertheless, classroom observations revealed that students in the experimental group participated in more active discussions, particularly when comparing information obtained through AI interactions and discussing differences between generated responses. These activities indicate that AI could function not only as an individual learning resource but also as a stimulus for interpersonal communication and collaborative knowledge construction (Heilporn et al., 2021). Students were provided with opportunities to share their interpretations, discuss alternative explanations, and examine different approaches to solving learning problems.

The findings suggest that the social contribution of AI depends substantially on how teachers structure collaborative learning activities. When AI is used exclusively for individual task completion, its contribution to social interaction may remain limited. However, when AI-generated responses become shared objects of discussion and evaluation, the technology can facilitate communication and collaborative problem-solving. This interpretation is consistent with Kim et al. (2022), who emphasized that student–AI collaboration depends on appropriate learning design and a culture of collaborative learning. Therefore, AI-assisted Informatics learning should incorporate opportunities for peer discussion and collective evaluation rather than focusing exclusively on individual interactions between students and AI.

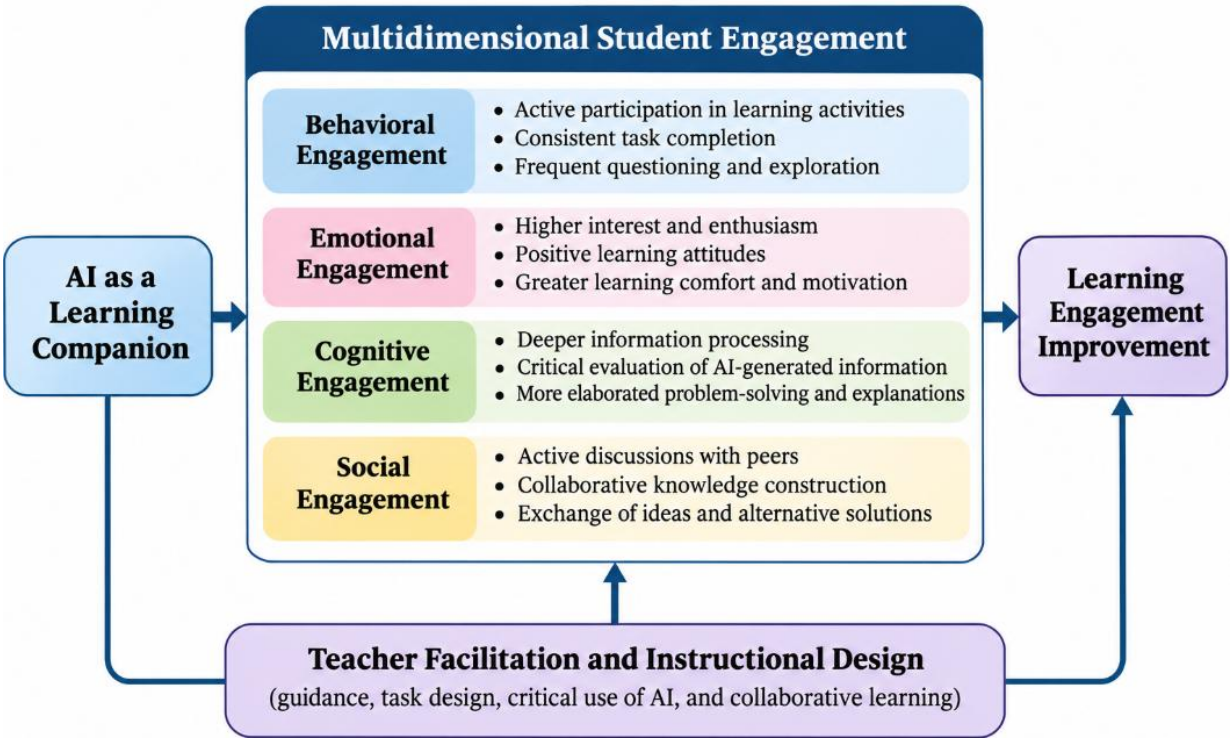

Figure 4. Multidimensional Student Engagement Framework in AI-Assisted Informatics Learning

3. Integrative Interpretation of Multidimensional Student Engagement

Taken together, the findings demonstrate that AI-assisted Informatics learning was associated with favorable characteristics across all four dimensions of student engagement. However, the observed contributions were not identical. Cognitive and behavioral engagement emerged as the most prominent dimensions based on the findings reported in the original study. Behavioral engagement was reflected in students' increased participation, independent task completion, and questioning behavior, whereas cognitive engagement was demonstrated through more elaborated responses, deeper explanations, and stronger justification of learning outcomes. Emotional engagement was reflected in students' greater interest, enthusiasm, and learning comfort, while social engagement was demonstrated through more active discussions and the exchange of ideas among students. These findings are also consistent with the study's overall conclusion that cognitive and behavioral engagement showed the most prominent improvement.

From a pedagogical perspective, these findings indicate that AI should not be positioned merely as an automated information provider but rather as a learning companion that facilitates active knowledge construction (Chang et al., 2023; Kim et al., 2022). Its contribution becomes more meaningful when students are encouraged to question, evaluate, compare, and reflect on AI-generated information. Such an approach creates opportunities to strengthen students' independent learning behaviors while maintaining the importance of teacher facilitation and peer interaction. This perspective is particularly relevant to vocational education,

where learning activities should integrate conceptual understanding, practical problem-solving, and collaborative competencies.

Furthermore, the findings highlight the importance of designing AI-supported learning environments that balance individual technological assistance with meaningful classroom interaction. Teachers need to establish clear guidelines regarding the appropriate use of AI, particularly in verifying information accuracy, developing independent solutions, and avoiding excessive dependence on generated answers (Celik et al., 2022; Walter, 2024). The integration of AI should therefore be accompanied by instructional strategies that promote critical digital literacy, reflective thinking, and collaborative learning. This is consistent with the findings of Lo et al. (2024) and Hou et al. (2025), which collectively emphasize the importance of guided AI utilization in developing meaningful educational experiences.

Overall, the multidimensional analysis suggests that AI-assisted Informatics instruction offers pedagogical opportunities to strengthen students' behavioral, emotional, cognitive, and social engagement. Nevertheless, the findings concerning individual dimensions are primarily supported by observational evidence, questionnaire descriptions, and learning assignment documentation rather than separate statistical effect estimates. Therefore, the identification of cognitive and behavioral engagement as the most prominent dimensions should be interpreted as a qualitative finding within the present study. Future investigations should employ dimension-specific quantitative measurements and larger participant samples to establish more precise estimates of the contribution of AI to each engagement dimension. These findings reinforce the importance of integrating AI through structured pedagogical approaches that support not only technological utilization but also students' active participation, emotional involvement, intellectual development, and collaborative learning.

Conclusion

This study demonstrates that the integration of Artificial Intelligence (AI) as a learning companion has a positive and statistically significant contribution to student engagement in Informatics education at the vocational high school level. The experimental group achieved a higher posttest mean score (69.38) than the control group (65.76), with improvements of 5.17 and 1.04 points, respectively. The independent samples t-test confirmed a statistically significant difference between the two groups ($t = 2.038$, $p = 0.047$), while the Cohen's d coefficient of 0.58 indicated a moderate effect. These findings suggest that AI-assisted instruction offers a meaningful pedagogical advantage over conventional learning approaches in supporting student engagement.

The multidimensional analysis further indicates that the contribution of AI-assisted learning extends across behavioral, emotional, cognitive, and social engagement. Behavioral engagement was reflected in more active classroom participation, questioning, and independent task completion. Emotional engagement was associated with greater learning interest, enthusiasm, and comfort, while cognitive engagement was demonstrated through more elaborated responses, critical evaluation of AI-generated information, and

problem-solving activities. Social engagement was reflected in classroom discussions, collaborative learning, and the exchange of ideas among students. Among these dimensions, behavioral and cognitive engagement emerged as the most prominent based on the reported observations and learning evidence.

The findings highlight that the educational value of AI does not depend solely on technological availability but also on its pedagogical integration. Positioning AI as a learning companion, rather than a substitute for independent thinking or teacher instruction, creates opportunities for more interactive, reflective, and student-centered learning experiences. Therefore, teachers play an essential role in guiding students to critically evaluate AI-generated information, develop independent solutions, and engage in meaningful collaborative activities. This approach is particularly relevant to vocational education, where students are expected to develop practical competencies alongside critical thinking and problem-solving abilities.

Despite these promising findings, the study was conducted within a single vocational high school involving a relatively limited sample of 49 students. Furthermore, the multidimensional findings were primarily supported by descriptive and observational evidence rather than separate statistical effect estimates for each engagement dimension. Future research should therefore involve larger and more diverse populations, extended intervention periods, and dimension-specific quantitative measurements to establish a more comprehensive understanding of AI's contribution to student engagement. Further investigations may also examine how different AI applications and pedagogical strategies influence students' learning independence, critical digital literacy, and vocational competencies.

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