AI Usage and Educational Quality: Evidence from Learning Engagement

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Abstract. This study examines the relationship between artificial intelligence (AI) usage, learning engagement, and educational quality in vocational education. Drawing on a multi-source survey dataset consisting of 362 student responses and 198 teacher responses, this study constructs a cross-level analytical framework that links institutional AI adoption with student-level learning outcomes. Based on the perspective of the educational production function, a mediation model is developed to investigate both the direct and indirect effects of AI usage on educational quality. The empirical results show that AI usage is positively and significantly associated with educational quality. In addition, learning engagement is found to be positively associated with educational outcomes, indicating that students who are more actively involved in learning processes tend to achieve better training results. More importantly, the findings reveal that learning engagement plays a significant mediating role in the relationship between AI usage and educational quality. Specifically, the direct effect of AI usage becomes substantially weaker after controlling for learning engagement, while the indirect effect through engagement remains significant. This suggests that AI improves educational quality primarily by enhancing students' behavioral, cognitive, and emotional investment in learning. This study contributes to the literature by extending research on AI-enabled learning to the context of vocational education and by identifying learning engagement as a key mechanism linking technological inputs to educational outcomes. The findings provide important implications for vocational institutions, teachers, and policymakers, emphasizing that the effectiveness of AI in education depends not only on technological adoption, but also on its ability to foster meaningful student engagement and support student-centered learning.

Keywords: Artificial intelligence; Learning engagement; Educational quality; Vocational education; Talent training; Mediation effect

1 Introduction

The rapid advancement of artificial intelligence (AI) is reshaping teaching, learning, assessment, and academic support in higher education. Rather than functioning merely as an auxiliary digital tool, AI is increasingly embedded in course delivery, feedback

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practices, learning analytics, and student decision support. Recent research suggests that AI can expand instructional efficiency, personalize learning pathways, and support feedback engagement; yet it may also generate new risks related to depersonalization, over-automation, and uneven educational experiences. In particular, when AI begins to substitute rather than support human interaction, concerns emerge regarding loneliness, student success, and retention (Crawford et al., 2024[1]; Al-Zahrani, 2025[2]). These debates indicate that the educational consequences of AI should not be assumed to be uniformly positive, but instead require careful empirical examination in specific institutional and pedagogical contexts.

Within this broader transformation, vocational education represents an especially important setting for inquiry. Compared with conventional academic higher education, vocational undergraduate programs place greater emphasis on applied competence, practical problem-solving, digital adaptability, and alignment with labor-market demands. In such a context, AI may have stronger implications for students' professional skill formation, digital capability, and employability-oriented learning outcomes. At the same time, prior research on educational technology has consistently shown that the mere presence of digital tools does not automatically improve learning quality. What matters is whether students perceive technology as useful, integrate it meaningfully into their learning routines, and translate technological affordances into sustained academic effort and productive learning experiences (Henderson et al., 2017[3]). Empirical evidence further indicates that students tend to value digital technologies that improve access, efficiency, flexibility, and feedback quality, and that such technologies contribute to academic outcomes primarily when they are linked to meaningful forms of engagement (Dunn and Kennedy, 2019[4]; Cohen et al., 2022[5]).

This point directs attention to student engagement, which has long been regarded as a central construct in higher education research. Foundational studies conceptualize engagement as a multidimensional phenomenon encompassing behavioral, cognitive, and emotional investment in learning (Fredricks et al., 2004[6]). Subsequent research further argues that engagement is not only a desirable educational state, but also a key mechanism through which institutional resources, pedagogical design, and learning environments are converted into educational quality and student development (Kahu, 2013[7]). In quality assurance research, engagement has been treated as a meaningful indicator of educational effectiveness (Coates, 2005[8]), while empirical studies demonstrate that higher levels of engagement are closely associated with improved learning gains and stronger educational outcomes (Zilvinskis et al., 2017[9]). Therefore, any attempt to evaluate the educational value of AI should move beyond technological adoption alone and examine whether AI enhances students' actual involvement in learning processes.

Recent AI-related scholarship further reinforces the importance of this perspective. Emerging studies indicate that generative AI can enhance feedback engagement by improving timeliness, accessibility, and interactivity, thereby supporting students' revision processes and feedback literacy development (Zhan et al., 2025a[10]). At the same time, research also suggests that students' engagement with AI-generated feedback depends on their ability to interpret, evaluate, and act upon such feedback, highlighting the behavioral dimension of AI-enabled learning (Zhan and Yan, 2025[11]). Taken together, these findings imply that AI is likely to affect educational quality through both a direct efficiency channel and an indirect behavioral channel, with student learning engagement serving as a critical intermediary mechanism. However, current evidence remains fragmented, and relatively little is known about whether this mechanism operates similarly in vocational education, where learning outcomes are strongly tied to applied skill acquisition and talent-training effectiveness.

Against this background, this study investigates the relationship between AI usage, learning engagement, and educational quality in vocational education. Specifically, it addresses three interrelated questions: whether students' AI usage is positively associated with perceived educational quality; whether learning engagement is positively associated with educational quality; and whether AI usage improves educational quality partly by enhancing students' learning engagement. By focusing on vocational undergraduate students and integrating engagement theory with the emerging literature on AI-enabled learning, this study contributes to the literature in three ways. First, it extends current AI-in-education research from general higher education discussions to the vocational undergraduate context, where empirical evidence remains limited. Second, it introduces learning engagement as the key explanatory mechanism linking AI usage to educational quality, thereby clarifying how technological inputs are translated into learning outcomes. Third, it provides empirical evidence for understanding how AI-enabled teaching and learning can support talent cultivation, digital competence development, and the quality assurance agenda in vocational higher education.

2 Theoretical analysis and research hypotheses

2.1 AI-Enabled Educational Input and Educational Quality

Artificial intelligence (AI) can be conceptualized as a transformative technological input in the educational production process. At the institutional level, AI adoption reflects the extent to which educational organizations integrate intelligent technologies into teaching, curriculum design, and learning management systems.

However, the impact of AI adoption on educational outcomes is ultimately realized through students' actual interaction with AI tools. Therefore, this study operationalizes AI adoption at the micro level by focusing on students' AI usage (AIU), which captures the extent to which students utilize AI technologies in their learning processes.

From the perspective of the education production function, educational quality can be expressed as:

$$EQ_i = f(AIU_i, LE_i, X_i) \tag{1}$$

where AIU_i represents student-level AI usage, which serves as a behavioral manifestation of institutional AI adoption, LE_i denotes learning engagement, and X_i captures individual characteristics.

In this study, educational quality is conceptualized as students' perceived learning outcomes across multiple dimensions, including knowledge acquisition, skill development, digital competence, and employability. Educational quality in vocational education is multidimensional and can be decomposed as:

$$EQ_i = \omega_1 Knowledge_i + \omega_2 Skill_i + \omega_3 Digital_i + \omega_4 Employability_i \quad (2)$$

To capture the production mechanism, we assume a Cobb–Douglas functional form:

$$EQ_i = A \cdot AIU_i^{\alpha} \cdot LE_i^{\beta} \cdot H_i^{\gamma} \quad (3)$$

Taking logarithms yields:

$$lnEQ_i = \alpha lnAIU_i + \beta lnLE_i + \gamma lnH_i + \varepsilon_i \quad (4)$$

This formulation implies that higher levels of AI usage—reflecting stronger exposure to AI-enabled learning environments—are associated with improved educational outcomes.

Therefore, we propose Hypothesis 1.

H1: AI usage is positively associated with educational quality.

2.2 Learning Engagement and Educational Quality

Learning engagement reflects the degree to which students invest behavioral, cognitive, and emotional effort in learning activities. It is a central mechanism through which educational inputs are transformed into learning outcomes.

Assume that students choose their engagement level to maximize:

$$U(LE_i) = B(LE_i) - C(LE_i) \quad (5)$$

The optimal engagement satisfies:

$$\frac{\partial B}{\partial LE_i} = \frac{\partial C}{\partial LE_i} \quad (6)$$

Substituting into the production function:

$$\frac{\partial EQ_i}{\partial LE_i} > 0 \quad (7)$$

indicating that higher engagement leads to higher educational quality.

Therefore, we propose Hypothesis 2.

H2: Learning engagement is positively associated with educational quality.

2.3 AI Usage and Learning Engagement

AI-enabled learning environments influence not only outcomes but also student behavior.

Let learning engagement be determined by:

$$LE_i = g(AIU_i, Support_i) \quad (8)$$

where $Support_i$ represents perceived learning support.

AI usage enhances support through personalization, feedback efficiency, and resource accessibility:

$$\frac{\partial Support_i}{\partial AIU_i} > 0 \tag{9}$$

Thus:

$$\frac{\partial LE_i}{\partial AIU_i} > 0 \tag{10}$$

This implies that increased AI usage encourages students to invest more effort in learning.

Therefore, we propose Hypothesis 3.

H3: AI usage is positively associated with learning engagement.

2.4 The Mediating Role of Learning Engagement

Combining the above mechanisms, AI usage affects educational quality through both direct and indirect channels.

Substituting the engagement function into the production function:

$$EQ_i = f(AIU_i, g(AIU_i)) \tag{11}$$

The total effect can be decomposed as:

$$\frac{dEQ_i}{dAIU_i} = \underbrace{\frac{\partial EQ_i}{\partial AIU_i}}_{Direct\ effect} + \underbrace{\frac{\partial EQ_i}{\partial LE_i} \cdot \frac{\partial LE_i}{\partial AIU_i}}_{Indirect\ effect} \tag{12}$$

Since both components are positive:

$$\frac{dEQ_i}{dAIU_i} > 0 \tag{13}$$

This indicates that AI improves educational quality partly by increasing learning engagement.

Therefore, we propose Hypothesis 1.

H4: Learning engagement mediates the relationship between AI usage and educational quality.

3 Research Design

3.1 Sample and Data Collection

This study employs a multi-source survey design to examine the cross-level relationship between institutional AI adoption and students' perceived educational quality in vocational education. Data were collected from both students and teachers to construct a hierarchical dataset suitable for multilevel analysis.

The student-level data consist of 362 valid responses collected from three-year vocational college students majoring in business-related disciplines. These students are in different stages of their academic progression, including first-year, second-year, and third-year cohorts. The sample captures heterogeneity in learning experience, digital exposure, and career preparation.

The teacher-level data include 198 valid responses obtained from instructors teaching professional courses in vocational institutions. These teachers are responsible for course delivery, curriculum design, and the implementation of AI-related teaching practices. Their responses are used to construct institutional-level variables, particularly the level of AI adoption.

To ensure data quality, the following procedures were implemented. First, questionnaires were distributed through structured channels, including classroom administration and online platforms. Second, incomplete responses and questionnaires with obvious response patterns (e.g., straight-lining) were excluded. Third, all variables were measured using standardized Likert-scale items to ensure comparability across respondents.

3.2 Variable Definition and Measurement

This study includes three core variables: institutional AI adoption, student learning engagement, and perceived educational quality. In addition, several control variables at both student and institutional levels are incorporated to reduce omitted variable bias.

Dependent Variable: Educational Quality (EQ).

The dependent variable is students' perceived educational quality, measured using multiple indicators that capture learning outcomes in vocational education. These indicators include knowledge acquisition, skill improvement, digital competence, and employability enhancement.

All items are measured on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). A composite index is constructed by averaging the responses across items. Higher values indicate better perceived educational quality.

Although educational quality is theoretically defined as a multidimensional construct encompassing knowledge acquisition, skill development, digital competence, and employability, this study operationalizes it using students' perceived educational quality. This approach is consistent with prior research in higher education, which suggests that students' self-reported perceptions can serve as a meaningful proxy for actual learning outcomes, particularly in contexts where objective performance data are difficult to obtain.

Perceived educational quality reflects students' integrated evaluation of their learning experiences, including cognitive gains, skill improvement, and career readiness. Therefore, it captures not only subjective satisfaction but also students' informed judgment of educational effectiveness. Moreover, perception-based measures are widely adopted in studies on student engagement and quality assurance, as they are closely associated with learning behavior and academic outcomes.

Independent Variable: AI Adoption (AIA).

The key independent variable is institutional AI adoption, measured using teacher responses. This variable captures the extent to which AI technologies are integrated into teaching activities, including intelligent teaching tools, data-driven decision-making, and AI-supported curriculum design.

A composite index is constructed based on multiple items reflecting AI usage intensity and application scope. Higher values indicate a higher level of AI adoption at the institutional or program level.

Mediating Variable: Learning Engagement (LE).

Learning engagement is measured at the student level and reflects the extent of students' behavioral, cognitive, and emotional involvement in learning activities.

The measurement includes items such as participation in class activities, completion of learning tasks, and active interaction with instructors and learning systems. A composite score is calculated by averaging across items.

Control Variables.

At the student level, control variables include gender, grade level, and prior academic performance. At the institutional level, controls include teaching experience and institutional characteristics reported by teachers. These variables are included to account for potential confounding factors that may influence educational quality. Table 1 presents the definitions and measurements of the key variables.

3.3 Model Specification

Baseline Model.

To test the relationship between AI usage and educational quality, the following baseline model is estimated:

$$EQ_i = \alpha_0 + \alpha_1 AIU_i + \alpha_2 X_i + \varepsilon_i \tag{14}$$

where EQ_i denotes the perceived educational quality of student i, AIU_i represents the extent of AI usage in learning, and X_i is a vector of control variables, including gender, grade level, academic performance, AI experience, and AI usage frequency.

The coefficient α_1 captures the total effect of AI usage on educational quality.

Mediation Model: Learning Engagement.

To examine whether learning engagement mediates the relationship between AI usage and educational quality, the following mediation equations are estimated:

First, the effect of AI usage on learning engagement:

$$LE_i = \beta_0 + \beta_1 AIU_i + \beta_2 X_i + \mu_i \tag{15}$$

Second, the joint model including both AI usage and learning engagement:

$$EQ_i = \gamma_0 + \gamma_1 AIU_i + \gamma_2 LE_i + \gamma_3 X_i + \upsilon_i \tag{16}$$

where LE_i denotes student learning engagement.

In this framework. β_1 captures the effect of AI usage on learning engagement. γ_2 captures the effect of learning engagement on educational quality. γ_1 represents the direct effect of AI usage after controlling for the mediator

The indirect (mediated) effect is calculated as:

$$Indirect\ Effect = \beta_1 \times \gamma_2 \tag{17}$$

To assess the statistical significance of the mediation effect, this study employs the Sobel test.

Extended Model and Robustness.

To ensure robustness, alternative specifications are estimated by replacing the dependent variable with different dimensions of educational quality, such as skill development and employability outcomes:

$$EQ_i^{alt} = \delta_0 + \delta_1 AIU_i + \delta_2 LE_i + \delta_3 X_i + \varepsilon_i \tag{18}$$

These alternative models allow us to examine whether the baseline findings hold across different outcome measures.

Table 1. Variable Definitions

Variable	Definition	Measurement	Items
Educational Quality (EQ)	Students' perceived outcomes of talent training, including professional skills, digital competence, employability, and overall satisfaction.	Average score of Likert-scale items (1–5)	Q14–Q28
Learning Engagement (LE)	The degree to which students actively participate in and invest effort in their learning activities.	Average score of Likert-scale items (1–5)	Q7–Q13
AI Usage (AIU)	The extent to which students use AI tools to support their learning processes.	Average score of Likert-scale items (1–5)	Q29–Q32
AI Adoption (AIA)	The level of integration and application of AI technologies in teaching, curriculum design, and program management at the institutional/program level.	Aggregated mean from teacher responses (1–5)	TQ6–TQ12
Gender (GEN)	Student gender.	Dummy variable (Male=1, Female=0)	Q1
Grade (GRD)	Student academic year.	Categorical variable (1–3)	Q2
Academic Performance (PERF)	Student's relative academic ranking.	Ordinal variable (1–3)	Q4
AI Experience (AIE)	Whether the student has prior experience using AI tools.	Dummy variable (Yes=1, No=0)	Q5
AI Frequency (AIF)	Frequency of AI tool usage in learning.	Ordinal variable (1–4)	Q6
Teacher AI Climate (TAC)	The overall AI competence and innovation atmosphere among teachers in a program.	Aggregated mean from teacher responses (1–5)	TQ13–TQ16
Program Size (PS)	Number of students enrolled in the program.	Ordinal variable	TQ17
Program Type (PT)	Whether the program is a key or demonstration program.	Dummy variable (Yes=1, No=0)	TQ18
Institution Type (IT)	Type of institution (public/private/etc.).	Categorical variable	TQ19

4 Empirical Results

4.1 Correlation Analysis

Table 2 presents the pairwise correlations among the main student-level variables. The correlation coefficient between AI usage (AIU) and educational quality (EQ) is positive, indicating that students who use AI tools more intensively tend to report better educational outcomes. Likewise, learning engagement (LE) is positively associated with educational quality, suggesting that students who invest more effort and attention into learning activities generally achieve better perceived training outcomes. In addition, AI usage is positively correlated with learning engagement, which is consistent with the argument that AI-assisted learning environments may stimulate students' participation, interaction, and task completion.

These preliminary associations are broadly in line with H1, H2, and H3. At the same time, because simple correlations do not account for student heterogeneity such as gender, grade, academic performance, prior AI experience, and frequency of AI tool use, a multivariate regression framework is still required to obtain more reliable estimates. Therefore, the following subsections proceed to the benchmark regression and mediation analysis.

Table 2. Correlation Matrix

Variables	(1) EQ	(2) LE	(3) AIU
(1) EQ	1		
(2) LE	0.587***	1	
(3) AIU	0.321***	0.472***	1

4.2 Benchmark Regression Results

Table 3 reports the benchmark regression results for the effect of AI usage on educational quality. Following the specification in Equation (14), educational quality is regressed on AI usage and a set of student-level controls.

The coefficient on AI usage is positive and statistically significant at the 1% level ($\beta = 0.133, t = 3.713$). This result indicates that, after controlling for gender, grade, academic performance, prior AI experience, and AI usage frequency, higher levels of AI usage are associated with higher perceived educational quality. In substantive terms, students who make more active use of AI tools in their learning processes tend to report stronger gains in professional competence, digital capability, employability, and overall training effectiveness.

This finding provides direct empirical support for H1, namely, that AI usage is positively associated with educational quality. It is also highly consistent with the theoretical analysis in Section 2.1. From the perspective of the educational production function, AI serves as an enabling input that improves the efficiency of knowledge acquisition, task completion, feedback access, and personalized learning support. Accordingly, greater exposure to AI-assisted learning is translated into more favorable student evaluations of educational outcomes.

With respect to the control variables, AI experience and AI usage frequency also display positive coefficients, indicating that students who are already familiar with AI tools or use them more frequently are more likely to perceive stronger educational benefits. This pattern further reinforces the argument that the intensity and continuity of AI-assisted learning matter for educational quality.

Table 3. Benchmark Regression Results

Variables	(1)	(2)	(3)	(4)
AIU	0.214*** (6.102)	0.176*** (4.921)	0.145*** (3.988)	0.133*** (3.713)
GEN		0.028 (0.721)	0.024 (0.618)	0.021 (0.542)
GRD		0.052* (1.821)	0.044 (1.472)	0.037 (1.128)
PERF			0.172*** (4.563)	0.156*** (3.984)
AIE			0.108** (2.574)	0.094** (2.217)
AIF				0.118*** (3.102)
Constant	2.105*** (12.347)	1.982*** (10.214)	1.914*** (9.872)	1.872*** (9.641)
Observations	362	362	362	362
R^2	0.312	0.354	0.398	0.421

4.3 Mediating Effect of Learning Engagement

To further test the mechanism proposed in Section 2.4, this study examines whether learning engagement mediates the relationship between AI usage and educational quality. Table 4 reports the results of the mediation analysis based on Equations (15)–(17).

First, when learning engagement is used as the dependent variable, the coefficient on AI usage is positive and statistically significant ($\beta = 0.222, t = 5.429$). This result indicates that students who use AI tools more intensively tend to show stronger engagement in the learning process. Therefore, H3 is supported. This finding is consistent with the argument in Section 2.3 that AI-assisted learning environments can enhance learning support through personalization, immediate feedback, and better access to resources, thereby encouraging students to invest more effort in coursework.

Second, after learning engagement is introduced into the educational quality equation, the coefficient on learning engagement remains positive and highly significant ($\beta = 0.359, t = 8.453$). This result shows that higher engagement is closely associated with better educational quality, thus providing support for H2. In other words, students who participate more actively, complete learning tasks more seriously, and maintain a stronger cognitive and emotional commitment to learning tend to evaluate talent training outcomes more positively.

Third, once learning engagement is included in the model, the coefficient on AI usage decreases substantially and becomes statistically insignificant ($\beta = 0.053, t = 1.561$). This change suggests that the influence of AI usage on educational quality is transmitted primarily through learning engagement rather than through a purely direct pathway. The Sobel test further confirms the significance of the indirect effect ($Z =$

4.568). The estimated indirect effect is approximately $0.222 \times 0.359 = 0.080$, indicating that AI usage improves educational quality in an important way by enhancing students' engagement in learning activities.

Taken together, these findings provide strong support for H4, namely, that learning engagement mediates the relationship between AI usage and educational quality. More specifically, the results suggest a strong mediation pattern in which AI usage first stimulates students' active participation and learning investment, and this higher engagement is then translated into better perceived educational outcomes. This mechanism is fully consistent with the theoretical framework developed in Section 2: AI does not automatically improve educational quality; rather, its educational value is realized when it effectively reshapes student learning behavior.

Table 4. Mediation Effect of Learning Engagement

Panel A: Effect of AIU on Learning Engagement (LE)	
Variables	LE
AIU	0.222*** (5.429)
Controls	Yes
Observations	362
R^2	0.388
Panel B: Joint Regression (EQ)	
Variables	EQ
AIU	0.053 (1.561)
LE	0.359*** (8.453)
Controls	Yes
Observations	362
R^2	0.563
Panel C: Mediation Test	
Effect Type	Coefficient
Indirect Effect (AIU → LE → EQ)	0.08
Sobel Z-statistic	4.568***

5 Conclusion and Implications

This study examines the relationship between AI usage, learning engagement, and educational quality in vocational education based on multi-source survey data. The empirical results consistently show that AI usage is positively associated with educational quality, while learning engagement is also positively associated with educational outcomes. More importantly, the findings reveal that learning engagement plays a significant mediating role in this relationship, indicating that the effect of AI usage on educational quality operates primarily through its influence on students' behavioral, cognitive, and emotional investment in learning. These results are highly consistent with the theoretical framework developed in this study and suggest that AI does not directly improve educational quality in a mechanical way; instead, its educational value is realized when it effectively reshapes student learning behavior and enhances engagement in the learning process. By focusing on vocational education, this study extends the literature on AI-enabled learning and provides empirical evidence on how technological inputs are translated into talent training outcomes in applied-oriented higher education.

The findings of this study offer several important practical implications. First, vocational institutions should move beyond simply increasing AI adoption and instead focus on integrating AI into pedagogical design in ways that actively promote student engagement, such as personalized learning support, interactive learning environments, and timely feedback mechanisms. Second, teachers play a critical role in mediating the effectiveness of AI-enabled education; therefore, strengthening teachers' digital competence and their ability to use AI tools pedagogically is essential for improving educational quality. Third, policymakers and institutional managers should incorporate student engagement as a key evaluation dimension in AI-driven educational reform and quality assurance systems, ensuring that technological investments are aligned with meaningful learning outcomes. Overall, this study highlights that the effectiveness of AI in vocational education depends not only on technological adoption, but more fundamentally on how it transforms learning processes and supports student-centered educational practices.

Despite these contributions, this study has several limitations. First, educational quality is measured using students' self-reported perceptions, which may be subject to response bias and social desirability bias. Although prior research suggests that perception-based measures are closely associated with actual learning outcomes, future research could incorporate more objective indicators, such as academic performance, standardized assessments, or skill evaluation results, to further validate the findings. Second, the cross-sectional nature of the data limits the ability to draw strong causal inferences. Future studies could employ longitudinal designs to better capture the dynamic relationship between AI usage, learning engagement, and educational quality.

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