



Advancing SDG 4 Through AI-Integrated Deep Learning Project-Based Learning: Enhancing Critical Thinking Skills and Scientific Literacy Among Primary School Teacher Education Students

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Abstract: This study examined the effect of an AI-integrated Deep Learning Project-Based Learning model on the critical thinking skills and scientific literacy of Primary School Teacher Education students at a university in Indonesia. A quasi-experimental non-equivalent control group design was employed involving 156 students, with 78 students in the experimental group and 78 students in the control group. Data were collected through critical thinking tests, scientific literacy tests, and a learning engagement questionnaire, then analysed using independent samples t-tests, N-Gain, Cohen's d, and SEM-PLS. The experimental group achieved higher mean scores in critical thinking skills than the control group (84.28 vs. 71.33) and higher scientific literacy scores (83.10 vs. 71.50). The N-Gain values for critical thinking were 0.71 in the experimental group and 0.46 in the control group, while scientific literacy N-Gain values were 0.69 and 0.47, respectively. Cohen's d values indicated very large effects for critical thinking skills (4.23) and scientific literacy (4.04). SEM-PLS showed positive relationships between the learning model and engagement ($\beta = 0.72$), engagement and critical thinking ($\beta = 0.55$), engagement and scientific literacy ($\beta = 0.52$), as well as direct effects on critical thinking ($\beta = 0.68$) and scientific literacy ($\beta = 0.65$). These findings indicate that the model supports meaningful, technology-enhanced learning.

Keywords: Artificial intelligence; Critical thinking skills; Deep learning; Learning engagement; Project-based learning; Scientific literacy

Introduction

Recent educational transformation has increasingly emphasised the need for students to master critical thinking skills, scientific literacy, digital competence, and the ability to solve complex real-world problems. Rehman et al. (2024a), Walter (2024), and Bond et al. (2020) emphasised that twenty-first-century learning should support student engagement, responsible technology use, and meaningful learning experiences. In the context of science education, Chen & Yang (2021),

Guo et al. (2020), and Hafizah et al. (2024) showed that active, contextual, and project-based learning can strengthen higher-order thinking skills. This direction is also aligned with Sustainable Development Goal 4 (SDG 4), which promotes inclusive, equitable, and quality education. In Indonesia, Putri et al. (2025), Alfiah et al. (2025), and Pratama et al. (2025) reported that scientific literacy needs to be continuously strengthened through contextual and project-based science learning. Therefore, science learning in higher education should not merely transfer scientific concepts but should also train students to analyse evidence, evaluate information,

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construct scientific explanations, and make reasoned decisions in real-life contexts.

Critical thinking skills and scientific literacy are two essential competencies in science education. According to Hafizah et al. (2024), critical thinking is closely related to students' ability to analyse arguments, evaluate evidence, and solve problems, while Walter (2024) highlighted that critical thinking is increasingly important in the era of artificial intelligence. In the middle of science learning practice, scientific literacy requires students to understand scientific concepts, interpret data, explain phenomena scientifically, and apply knowledge to contextual problems. This view is supported by Putri et al. (2025), Fitriani et al. (2025), and Wisdayana et al. (2025), who showed that scientific literacy and critical thinking can be strengthened through learning that connects scientific concepts with real issues. Moreover, Chen & Yang (2021), Guo et al. (2020), and Rehman et al. (2024b) found that project-oriented learning can promote active investigation and higher-order thinking. Thus, critical thinking skills and scientific literacy should be developed simultaneously because scientifically literate students need critical reasoning to evaluate claims, interpret evidence, and respond to socio-scientific issues.

However, the development of critical thinking skills and scientific literacy remains a persistent problem in science learning. Bond et al. (2020), Kasneci et al. (2023), and Zhai et al. (2021) indicated that digital learning and artificial intelligence will not automatically improve learning outcomes if they are not integrated into appropriate pedagogical designs. In many classrooms, learning is still dominated by lecturer-centred explanations, memorisation, and routine assignments, which provide limited opportunities for students to investigate problems and construct scientific explanations. This condition tends to produce surface-level understanding rather than deep conceptual understanding. Harjono et al. (2025), Chomsun et al. (2025), and Kusumaningsih et al. (2025) also showed that students' scientific literacy and critical thinking skills require learning designs that include contextual problems, project activities, socio-scientific issues, and reflective evaluation. In line with Chen & Yang (2021), Guo et al. (2020), and Hafizah et al. (2024), the improvement of critical thinking and scientific literacy requires active learning models that connect scientific concepts with real-world problem solving.

This issue is especially important in Primary School Teacher Education programmes. Malagola et al. (2023) argued that Primary School Teacher Education students need strong critical thinking ability and understanding of basic science concepts because they will later become elementary school teachers. Rehman et al. (2024a), Bond et al. (2020), and Walter (2024) also emphasised that

future teachers need learning experiences that develop collaboration, digital competence, problem solving, and reflective thinking. In the context of science teacher preparation, prospective elementary teachers should be able to design learning that introduces scientific concepts, inquiry habits, and reasoning skills to young learners. If prospective teachers have weak critical thinking skills and limited scientific literacy, they may face difficulties in developing meaningful science learning for elementary school students. Studies by Putri et al. (2025), Fitriani et al. (2025), and Pratama et al. (2025) confirm that scientific literacy in Indonesian education contexts should be strengthened through contextual learning and authentic investigation. Therefore, improving critical thinking skills and scientific literacy among Primary School Teacher Education students is not only related to their academic achievement but also to the future quality of elementary science education.

The urgency of this study is supported by constructivist learning theory and cognitive learning principles. Piaget (1952) explained that knowledge is actively constructed through interaction with the environment, while Vygotsky (1978) emphasised social interaction, scaffolding, and the zone of proximal development as essential elements of learning. In contemporary instructional design, Sweller et al. (2019) explained that learning becomes more effective when cognitive load is managed so that students can focus on essential conceptual understanding. These theoretical perspectives are consistent with Chen & Yang (2021), Guo et al. (2020), and Hafizah et al. (2024), who showed that active and project-oriented learning can improve students' higher-order thinking. In science learning, Harjono et al. (2025), Nurtamam et al. (2025), and Wisdayana et al. (2025) also demonstrated that students need learning environments that allow them to investigate problems, collaborate, reflect, and build scientific understanding. Thus, science learning should integrate active knowledge construction, social collaboration, structured scaffolding, and cognitive support.

Project-Based Learning is one instructional model that is consistent with constructivist learning principles. Chen & Yang (2021), Guo et al. (2020), and Rehman et al. (2024b) explained that Project-Based Learning supports student-centred learning by engaging students in authentic projects, investigation, collaboration, product development, presentation, and reflection. In the middle of project activities, students are required to identify problems, collect information, analyse data, develop solutions, and communicate their findings. Evidence from JPPIPA also supports this view: Alfiah et al. (2025), Pratama et al. (2025), and Harjono et al. (2025) found that Project-Based Learning and STEM-integrated project

learning can improve scientific literacy and critical thinking because students connect scientific concepts with real-world problems. Similarly, Mutiara et al. (2024), Chomsun et al. (2025), and Wisdayana et al. (2025) showed that problem-based, project-based, and socio-scientific issue-based learning can strengthen critical thinking skills through contextual problem solving and evidence-based reasoning. Therefore, Project-Based Learning is relevant for developing scientific literacy and critical thinking skills in teacher education.

Nevertheless, Project-Based Learning does not automatically guarantee deep conceptual understanding. Guo et al. (2020), Chen & Yang (2021), and Hafizah et al. (2024) suggested that project activities must be designed carefully so that students do not only focus on completing project products but also understand the concepts and reasoning processes behind them. In this study, deep learning refers to a learning orientation that emphasises meaningful conceptual understanding, connections among ideas, reflective thinking, knowledge transfer, and metacognitive awareness. Nurtamam et al. (2025) showed that deep learning-based Project-Based Learning has a significant effect on students' scientific and critical thinking skills, while Kusumaningrum et al. (2025) highlighted the role of deep learning in improving critical thinking. This is also supported by Bond et al. (2020), Rehman et al. (2024a), and Walter (2024), who emphasised the importance of engagement, collaboration, and digital competence in meaningful learning. Thus, integrating deep learning into Project-Based Learning is expected to make project activities more conceptually meaningful, cognitively productive, and reflective.

The development of artificial intelligence provides new opportunities to strengthen science learning. Walter (2024), Kasneci et al. (2023), and Zhai et al. (2021) argued that artificial intelligence can support learning through feedback, adaptive assistance, information processing, and critical reflection, but its use must be guided by sound pedagogical principles. In science education, artificial intelligence can assist students in generating guiding questions, comparing alternative explanations, receiving formative feedback, and reflecting on scientific arguments. Recent JPPIPA studies have also shown the relevance of artificial intelligence and digital technologies in science learning; Aji et al. (2025), Pairunan et al. (2025), and Fathurrahman et al. (2025) reported that artificial intelligence-based learning media, e-learning modules, and Custom GPT models can support students' critical thinking skills. In addition, Antony et al. (2025), Kasman et al. (2025), and Nurwahidah et al. (2025) demonstrated that artificial intelligence, mobile learning, and technology-supported

modules can enhance analytical thinking, critical thinking, communication, and digital literacy. Therefore, in this study, artificial intelligence is positioned not merely as a technological tool but as a cognitive partner that supports scaffolding, feedback, inquiry, and reflection.

Student engagement is another important mechanism in explaining the effectiveness of innovative learning models. Bond et al. (2020), Rehman et al. (2024b), and Guo et al. (2020) emphasised that active engagement is strongly related to meaningful participation, collaboration, learning persistence, and academic achievement. In this study, learning engagement includes behavioural engagement, emotional engagement, and cognitive engagement. Behavioural engagement is reflected in active participation and task completion; emotional engagement is reflected in interest, motivation, and confidence; and cognitive engagement is reflected in deep thinking, self-regulation, and persistence in understanding complex ideas. This position is supported by Harjono et al. (2025), Pratama et al. (2025), and Nurtamam et al. (2025), who indicated that project-based and deep learning-oriented science instruction can stimulate active learning and scientific reasoning. Moreover, Walter (2024), Kasneci et al. (2023), and Pairunan et al. (2025) suggest that artificial intelligence-supported learning can be beneficial when it encourages students to reflect, verify information, and improve their reasoning. Therefore, learning engagement may mediate the relationship between AI-integrated Deep Learning Project-Based Learning and students' critical thinking skills and scientific literacy.

Although previous studies have examined Project-Based Learning, deep learning, artificial intelligence, critical thinking skills, and scientific literacy, most studies have investigated these elements separately. Chen & Yang (2021), Guo et al. (2020), and Hafizah et al. (2024) focused mainly on project-based or problem-based learning and higher-order thinking, while Walter (2024), Kasneci et al. (2023), and Zhai et al. (2021) emphasised artificial intelligence and digital learning in education. In JPPIPA, studies by Aji et al. (2025), Pairunan et al. (2025), and Fathurrahman et al. (2025) examined AI-supported learning and critical thinking, while Nurtamam et al. (2025), Pratama et al. (2025), and Harjono et al. (2025) focused on deep learning-based PjBL, STEM-integrated PjBL, and scientific literacy. However, limited studies have simultaneously integrated artificial intelligence, deep learning, Project-Based Learning, learning engagement, critical thinking skills, and scientific literacy in the specific context of Primary School Teacher Education students. This gap indicates the need for an integrated model that connects

pedagogy, cognition, technology, and engagement in one empirical framework.

The local gap addressed in this study is the need for an instructional model that can strengthen Primary School Teacher Education students' critical thinking skills and scientific literacy through meaningful, technology-supported, and project-based science learning. Malagola et al. (2023), Putri et al. (2025), and Fitriani et al. (2025) indicated that prospective teachers and students in Indonesian science education contexts still require stronger conceptual understanding, scientific reasoning, and critical evaluation. In the observed learning context, conventional instruction still tends to emphasise lecturer explanation and task completion, while students have limited opportunities to engage in deep inquiry, evidence-based reasoning, reflective discussion, and responsible use of digital technologies. This condition is inconsistent with the learning demands described by Rehman et al. (2024a), Bond et al. (2020), and Walter (2024), who emphasised engagement, digital competence, and meaningful learning as important components of twenty-first-century education. Therefore, learning innovation is needed not only to involve students in projects but also to guide them to understand scientific concepts deeply, manage cognitive processes effectively, and use artificial intelligence critically as learning support.

The novelty of this study lies in the development and empirical testing of an AI-integrated Deep Learning Project-Based Learning model to support SDG 4 in primary teacher education. Conceptually, this model integrates Project-Based Learning as the pedagogical structure, deep learning as the orientation for meaningful conceptual understanding, Cognitive Load Theory as the basis for managing learning complexity, and artificial intelligence as a cognitive partner for scaffolding, feedback, inquiry, and reflection. This conceptual integration is strengthened by Piaget (1952), Vygotsky (1978), and Sweller et al. (2019), who provide theoretical foundations for active knowledge construction, scaffolding, and cognitive load management. Empirically, this study extends the works of Nurtamam et al. (2025), Aji et al. (2025), and Pairunan et al. (2025) by simultaneously testing critical thinking skills, scientific literacy, and learning engagement within one SEM-PLS framework. In line with Chen & Yang (2021), Guo et al. (2020), and Rehman et al. (2024b), this study contributes to the development of innovative learning models that integrate pedagogy, cognition, technology, and engagement.

Based on this background, this study aims to analyse the effect of an AI-integrated Deep Learning Project-Based Learning model on the critical thinking skills and scientific literacy of Primary School Teacher Education students. Specifically, this study investigates

whether students who learn through AI-integrated Deep Learning Project-Based Learning achieve higher critical thinking skills and scientific literacy than students who learn through conventional instruction. Furthermore, this study examines whether learning engagement mediates the relationship between the learning model and students' learning outcomes. The findings are expected to contribute theoretically to technology-supported constructivist learning and practically to the improvement of science learning quality in teacher education programmes. This contribution is relevant to SDG 4 because it supports the development of quality, student-centred, and technology-enhanced science learning (Bond et al., 2020; Chen & Yang, 2021; Harjono et al., 2025; Nurtamam et al., 2025; Rehman et al., 2024a; Walter, 2024).

Method

Research Design

This study employed a quantitative approach using a quasi-experimental design with a non-equivalent control group design. A quasi-experimental design was selected because the research was conducted in a real classroom setting where full random assignment of individual students was not possible. This design is appropriate for educational intervention research because it allows researchers to compare the learning outcomes of an experimental group and a control group while maintaining the natural classroom structure (Creswell & Creswell, 2022; Fraenkel et al., 2023). The experimental group received AI-integrated Deep Learning Project-Based Learning, while the control group received conventional instruction. Both groups were given pre-tests and post-tests to measure students' critical thinking skills and scientific literacy.

The quasi-experimental design was used to examine the effectiveness of the intervention, while Structural Equation Modeling–Partial Least Squares (SEM-PLS) was used to analyse the structural relationships among the learning model, learning engagement, critical thinking skills, and scientific literacy. Therefore, each statistical technique had a different function. The independent samples t-test was used to examine post-test differences between the experimental and control groups. N-Gain was used to measure the improvement of students' scores from pre-test to post-test. Cohen's d was used to determine the practical magnitude of the treatment effect. SEM-PLS was used to examine direct and indirect relationships among variables, including the mediating role of learning engagement (Cohen, 1988; Hake, 1998; Hair et al., 2021; Sarstedt et al., 2021).

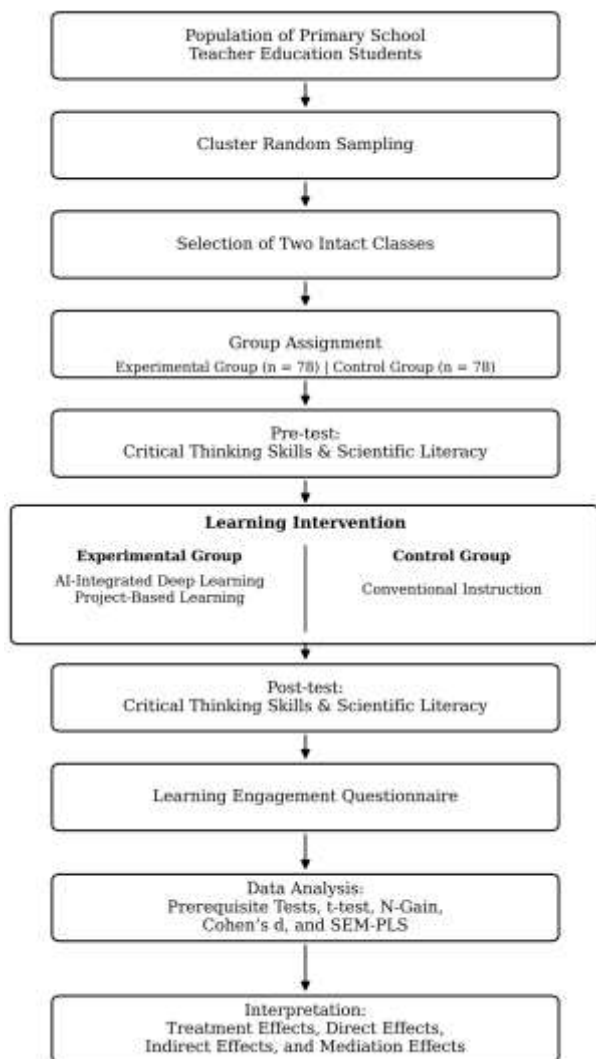


Figure 1. Research design flowchart

Participants and Sampling Technique

The population of this study consisted of Primary School Teacher Education students at a university in Indonesia. The sample was selected using cluster random sampling because the students were already organised into existing classes. Cluster random sampling is commonly used in educational research when individual randomisation is difficult to implement and intact classes are used as sampling units (Fraenkel et al., 2023). Two intact classes were randomly selected from the population. One class was assigned as the experimental group and the other as the control group.

The total sample consisted of 156 students, with 78 students in the experimental group and 78 students in the control group. The use of cluster random sampling was related to the quasi-experimental design because the study was conducted in natural classroom conditions. Meanwhile, the total sample size of 156 respondents was considered adequate for SEM-PLS analysis because it met the recommended sample size

for estimating a structural model with several latent variables and indicators. Hair et al. (2021) explain that SEM-PLS is suitable for analysing complex relationships among latent variables and can be applied in educational research when the objective is prediction and theory development.

In the SEM-PLS analysis, the learning model was treated as an exogenous variable. The experimental group was coded as 1, representing students who received AI-integrated Deep Learning Project-Based Learning, while the control group was coded as 0, representing students who received conventional instruction. Learning engagement was positioned as a mediating variable, while critical thinking skills and scientific literacy were treated as endogenous variables. This coding procedure was used to make the quasi-experimental group comparison compatible with the SEM-PLS structural model.

Learning Intervention

The experimental group was taught using AI-integrated Deep Learning Project-Based Learning. This intervention combined Project-Based Learning as the main pedagogical structure, deep learning as the orientation for meaningful conceptual understanding, and artificial intelligence as a cognitive partner that supported students through scaffolding, formative feedback, idea generation, source comparison, and reflective questioning. Project-Based Learning was used because it supports student-centred learning, collaboration, inquiry, and authentic problem-solving (Chen & Yang, 2021; Guo et al., 2020; Rehman et al., 2024b). Deep learning was embedded to ensure that project activities were not limited to product completion but also promoted conceptual understanding, knowledge transfer, and reflective reasoning. Cognitive Load Theory was used as the instructional design basis to manage learning complexity and help students focus on essential scientific concepts (Sweller et al., 2019).

Artificial intelligence was integrated as a learning support, not as a replacement for students' reasoning processes. In this study, AI was used to help students generate guiding questions, compare explanations, receive formative feedback, check the coherence of arguments, and reflect on scientific concepts. This approach is consistent with recent studies showing that AI-supported learning can strengthen critical thinking, engagement, and reflective learning when it is used within a pedagogically structured learning design (Kasneci et al., 2023; Walter, 2024; Zhai et al., 2021). The control group was taught using conventional instruction, which consisted mainly of lecturer explanation, question-and-answer activities, class discussion, and individual assignments without structured AI-supported project activities.

The intervention was conducted over 6–8 learning sessions. The learning activities in the experimental group were designed to help students identify contextual science problems, plan projects, conduct investigations, develop learning products, present findings, and reflect on their learning process. The syntax of the AI-integrated Deep Learning Project-Based Learning intervention is presented in Table 1.

Table 1. Syntax of AI-integrated deep learning project-based learning intervention

Learning phase	Lecturer activity	Student activity	AI integration	Deep learning orientation	Expected outcome
Problem orientation	The lecturer presents contextual science problems related to elementary science learning.	Students identify the main problem, formulate initial questions, and connect the problem with prior knowledge.	AI is used to generate guiding questions and explore possible explanations related to the problem.	Activating prior knowledge and connecting concepts with real-world phenomena.	Students are able to identify scientific problems and formulate inquiry questions.
Project planning	The lecturer guides students in designing project objectives, procedures, group roles, and expected products.	Students develop project plans, determine learning resources, and design investigation steps.	AI provides feedback on project feasibility, clarity of objectives, and possible investigation strategies.	Planning inquiry, organising concepts, and developing learning strategies.	Students are able to design a systematic and conceptually relevant project plan.
Investigation and data exploration	The lecturer facilitates group investigation and monitors students' inquiry process.	Students collect information, compare sources, analyse data, and discuss scientific explanations.	AI supports source comparison, provides scaffolding questions, and helps students check the logic of explanations.	Evidence-based reasoning, conceptual analysis, and critical evaluation.	Students are able to analyse evidence and construct scientific explanations.
Product development	The lecturer guides students in developing project outputs related to science learning.	Students create project products, revise explanations, and improve the accuracy of scientific content.	AI provides formative feedback on clarity, accuracy, coherence, and completeness of the project product.	Knowledge construction, refinement of ideas, and conceptual integration.	Students are able to produce scientifically accurate and meaningful learning products.
Presentation and argumentation	The lecturer facilitates presentation, peer feedback, and scientific discussion.	Students present project results, defend arguments, and respond to questions from peers.	AI is used to prepare reflection prompts and possible argument-checking questions.	Scientific communication, argumentation, and reflective reasoning.	Students are able to communicate scientific ideas and justify arguments based on evidence.
Reflection and evaluation	The lecturer guides students to evaluate their learning process and conceptual understanding.	Students reflect on what they learned, identify difficulties, and evaluate the role of AI in supporting learning.	AI supports self-assessment, metacognitive reflection, and revision of scientific explanations.	Metacognitive awareness, knowledge transfer, and deep conceptual understanding.	Students are able to reflect on learning processes and transfer knowledge to new contexts.

Research Instruments

The instruments used in this study consisted of a critical thinking skills test, a scientific literacy test, and a learning engagement questionnaire. The critical thinking skills test was developed in the form of higher-order thinking essay questions measuring analysis, evaluation, inference, interpretation, and argumentation. These indicators are consistent with the view that critical thinking involves analysing evidence, evaluating arguments, and making reasoned judgments (Facione, 2020; Walter, 2024).

The scientific literacy test was designed to measure students' ability to understand scientific concepts, interpret data, explain scientific phenomena, and apply scientific knowledge in contextual situations. Scientific literacy was used consistently throughout this study to avoid conceptual inconsistency with the research title, abstract, and keywords. The learning engagement questionnaire used a five-point Likert scale and measured three dimensions of engagement: behavioural engagement, emotional engagement, and cognitive engagement. Behavioural engagement referred to students' active participation and task completion.

Emotional engagement referred to students' interest, motivation, and confidence. Cognitive engagement referred to students' deep thinking, persistence, self-regulation, and effort to understand complex concepts. The multidimensional structure of engagement is consistent with previous research on student engagement in technology-supported learning (Bond et al., 2020).

Before being used in the main study, the instruments were reviewed by experts to ensure content validity. The empirical validity and reliability of the questionnaire indicators were then evaluated using the SEM-PLS measurement model. The evaluation included factor loading, Average Variance Extracted, Composite Reliability, and Cronbach's Alpha. These criteria are commonly used to assess convergent validity and internal consistency reliability in SEM-PLS studies (Hair et al., 2021; Sarstedt et al., 2021).

Data Collection Procedure

The data collection procedure consisted of three stages: preparation, implementation, and evaluation. In the preparation stage, the researcher developed learning materials, project scenarios, AI-supported learning activities, research instruments, and assessment rubrics. The instruments were reviewed by experts before implementation to ensure that the test items, questionnaire indicators, and project activities were aligned with the research objectives.

In the implementation stage, both the experimental and control groups were given pre-tests to measure their initial critical thinking skills and scientific literacy. The experimental group then received AI-integrated Deep Learning Project-Based Learning, while the control group received conventional instruction. After the intervention, both groups were given post-tests. The learning engagement questionnaire was administered after the intervention to measure students' behavioural, emotional, and cognitive engagement.

In the evaluation stage, the collected data were analysed using descriptive statistics, prerequisite tests, effectiveness testing, improvement analysis, effect size calculation, and SEM-PLS analysis. This step-by-step analysis was designed to ensure that the study could report not only whether the intervention was statistically effective but also how the learning model influenced students' outcomes through learning engagement.

Data Analysis

Data analysis was conducted in several stages. First, descriptive statistics were used to describe the mean, standard deviation, minimum score, maximum score, and category of each variable. Second, prerequisite tests were conducted to examine the assumptions of

parametric analysis. The normality test was conducted to determine whether the data were normally distributed, while the homogeneity test was conducted to examine the equality of variances between groups.

Third, an independent samples t-test was used to examine whether there were significant differences in post-test scores between the experimental and control groups. This analysis was appropriate because the study compared two independent groups after the intervention. If there were substantial differences in pre-test scores, ANCOVA could be used as an alternative analysis by controlling pre-test scores as covariates. However, when the pre-test scores between groups are relatively equivalent and the assumptions of normality and homogeneity are met, the independent samples t-test is appropriate for testing differences in post-test scores (Field, 2024).

Fourth, N-Gain analysis was used to determine the improvement in students' critical thinking skills and scientific literacy from pre-test to post-test. N-Gain is widely used in educational research to measure the degree of improvement by comparing actual gain with maximum possible gain (Hake, 1998). The N-Gain score was calculated using the following formula:

$$N\text{-Gain} = \frac{S_{\text{post}} - S_{\text{pre}}}{S_{\text{max}} - S_{\text{pre}}} \quad (1)$$

where:

S_{post} = post-test score

S_{pre} = pre-test score

S_{max} = maximum possible score

The interpretation of N-Gain was determined as follows:

$g > 0.70$ = high

$0.30 \leq g \leq 0.70$ = moderate

$g < 0.30$ = low

Fifth, Cohen's d was used to determine the magnitude of the treatment effect. Cohen's d complements significance testing because it provides information about the practical strength of the difference between the experimental and control groups (Cohen, 1988). The effect size was calculated using the following formula:

$$d = \frac{M_{\text{experimental}} - M_{\text{control}}}{SD_{\text{pooled}}} \quad (2)$$

where:

$M_{\text{experimental}}$ = mean score of the experimental group

M_{control} = mean score of the control group

SD_{pooled} = pooled standard deviation

The pooled standard deviation was calculated using the following formula:

$$SD_{\text{pooled}} = \sqrt{\frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}} \quad (3)$$

where:

n_1 = sample size of the experimental group

n_2 = sample size of the control group

SD_1 = standard deviation of the experimental group

SD_2 = standard deviation of the control group

The interpretation of Cohen's d was determined as follows:

$d = 0.20$ = small effect

$d = 0.50$ = medium effect

$d \geq 0.80$ = large effect

Sixth, SEM-PLS analysis was conducted to test the structural relationships among the learning model, learning engagement, critical thinking skills, and scientific literacy. SEM-PLS was selected because it is suitable for prediction-oriented analysis and for testing models involving latent variables and mediation effects (Hair et al., 2021; Sarstedt et al., 2021). The general formula is:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (4)$$

where:

SS_{res} = sum of squared residuals

SS_{tot} = total sum of squares

The interpretation of R^2 was determined as follows:

$R^2 = 0.25$ = weak

$R^2 = 0.50$ = moderate

$R^2 = 0.75$ = strong

Bootstrapping significance criteria in SEM-PLS were determined using the following decision rule $t > 1.96$; $p < 0.05$.

If both criteria are fulfilled, the relationship between variables is considered statistically significant at the 95% confidence level.

SEM-PLS Analysis

SEM-PLS analysis was conducted to examine the direct and indirect relationships among the variables. The analysis consisted of two stages: evaluation of the measurement model and evaluation of the structural model. This two-stage approach is recommended in SEM-PLS because the validity and reliability of the measurement model must be confirmed before interpreting the structural relationships among variables (Hair et al., 2021; Sarstedt et al., 2021).

The measurement model was evaluated using factor loading, Average Variance Extracted, Composite Reliability, Cronbach's Alpha, and discriminant validity. Indicators with factor loading values above 0.70 were considered valid. AVE values above 0.50 indicated adequate convergent validity. AVE was calculated using the following formula:

$$AVE = \frac{\sum_{i=1}^n \lambda_i^2}{n} \quad (5)$$

where:

λ_i = standardized factor loading of indicator i

n = number of indicators

Composite Reliability and Cronbach's Alpha values above 0.70 indicated adequate internal consistency. Discriminant validity was assessed using the Fornell-Larcker criterion and cross-loading values. In the Fornell-Larcker criterion, the square root of AVE for each construct must be greater than its correlation with other constructs. CR was calculated using the following formula:

$$CR = \frac{(\sum_{i=1}^n \lambda_i)^2}{(\sum_{i=1}^n \lambda_i)^2 + \sum_{i=1}^n \theta_i} \quad (6)$$

where:

λ_i = standardized factor loading of indicator i

θ_i = error variance of indicator i

The error variance was calculated as follows:

$$\theta_i = 1 - \lambda_i^2 \quad (7)$$

Composite Reliability is considered acceptable when $CR > 0.70$.

The structural model was evaluated using path coefficients, coefficient of determination, and bootstrapping. The coefficient of determination was used to determine the explanatory power of the model. The path coefficients were used to examine the direction and strength of the relationships among variables. The significance of the relationships was tested through bootstrapping with the criteria of ($t > 1.96$) and ($p < 0.05$). Mediation analysis was conducted to determine whether learning engagement mediated the relationship between the learning model and students' critical thinking skills and scientific literacy.

Result and Discussion

Results

Descriptive Analysis

Descriptive analysis was conducted to provide an overview of students' critical thinking skills, scientific literacy, and learning engagement in the experimental and control groups. The initial abilities of the two groups were relatively equivalent, as indicated by the similar mean pre-test scores before the intervention. After the implementation of the learning intervention, the experimental group achieved higher post-test scores than the control group in both critical thinking skills and scientific literacy.

The mean post-test score for critical thinking skills in the experimental group was 84.28, with a standard deviation of 3.58, while the control group obtained a mean score of 71.33, with a standard deviation of 2.42. The experimental group also achieved a higher mean score in scientific literacy, with a mean of 83.10 and a standard deviation of 3.20, compared with the control group, which obtained a mean score of 71.50 and a standard deviation of 2.50.

Table 2. Descriptive statistics of critical thinking skills and scientific literacy

Variable	Group	N	Mean	SD	Minimum	Maximum	Category
Critical thinking skills	Experimental	78	84.28	3.58	77	92	High
	Control	78	71.33	2.42	66	75	Moderate
Scientific literacy	Experimental	78	83.10	3.20	76	90	High
	Control	78	71.50	2.50	67	75	Moderate

*Prerequisite Tests***Table 3.** Summary of prerequisite test results

Variable	Normality Test p-value	Homogeneity Test p-value	Interpretation
Critical thinking skills	0.133 > 0.05	0.001 < 0.05	Normal but not homogeneous
Scientific literacy	0.078 > 0.05	0.001 < 0.05	Normal but not homogeneous

The normality test was conducted to determine whether the research data were normally distributed. The results showed that the significance values for all variables were greater than 0.05, indicating that the data met the normality assumption. The homogeneity test was conducted using Levene's test, and the significance values were also greater than 0.05. Therefore, the

variances between the experimental and control groups were considered homogeneous, and parametric statistical analysis could be conducted.

Improvement in Learning Outcomes

The improvement in students' learning outcomes was analysed using Normalized Gain scores. The experimental group obtained an N-Gain score of 0.71 for critical thinking skills, which was classified as high, while the control group obtained an N-Gain score of 0.46, which was classified as moderate. For scientific literacy, the experimental group obtained an N-Gain score of 0.69, while the control group obtained an N-Gain score of 0.47. Although the scientific literacy N-Gain score of the experimental group was close to the high category threshold, it remained within the moderate category based on the predetermined criteria.

Table 4. N-Gain scores of critical thinking skills and scientific literacy

Variable	Experimental Group	Category	Control Group	Category
Critical thinking skills	0.71	High	0.46	Moderate
Scientific literacy	0.69	Moderate	0.47	Moderate

These findings indicate that AI-integrated Deep Learning Project-Based Learning produced greater improvements in students' critical thinking skills and scientific literacy than conventional instruction.

Differences between the Experimental and Control Groups

A Welch's independent samples t-test was conducted to examine whether there were significant differences in post-test scores between the experimental and control groups. The results showed a statistically

significant difference in critical thinking skills between the experimental and control groups, ($t_{(154)} = 26.47$), ($p < 0.001$). The experimental group achieved a substantially higher mean score than the control group.

A statistically significant difference was also found in scientific literacy, ($t_{(154)} = 25.23$), ($p < 0.001$). These results indicate that the learning intervention had a significant effect on both critical thinking skills and scientific literacy.

Table 5. Welch's independent samples t-test results

Variable	Experimental Mean	Control Mean	Mean Difference	t-statistic	df	p-value
Critical thinking skills	84.28	71.33	12.95	26.47	154	< 0.001
Scientific literacy	83.10	71.50	11.60	25.23	154	< 0.001

Effect Size

Cohen's d was calculated to determine the practical magnitude of the intervention effect. The effect size for critical thinking skills was 4.23, while the effect size for scientific literacy was 4.04. Both values indicate very large effects, demonstrating that the differences between the experimental and control groups were not only statistically significant but also practically substantial.

Table 6. Effect size of the learning intervention

Variable	Cohen's d	Interpretation
Critical thinking skills	4.23	Very large effect
Scientific literacy	4.04	Very large effect

Evaluation of the Measurement Model

The measurement model was evaluated to assess the validity and reliability of the constructs used in the study. Convergent validity was examined using the

outer loading values and Average Variance Extracted (AVE), while internal consistency reliability was assessed using Composite Reliability and Cronbach's Alpha. The results presented in Table 7 show that all indicator loading values exceeded the recommended threshold of 0.70. The AVE values for all constructs were

greater than 0.50, indicating that each construct explained more than 50% of the variance in its indicators. In addition, the Composite Reliability and Cronbach's Alpha values exceeded 0.70, confirming adequate internal consistency reliability.

Table 7. Measurement model evaluation

Construct	Factor Loading Range	AVE	Composite Reliability	Cronbach's Alpha	Interpretation
Learning Engagement	0.957–0.967	0.928	0.975	0.960	Valid and reliable
Critical Thinking Skills	0.822–0.875	0.727	0.930	0.905	Valid and reliable
Scientific Literacy	0.822–0.863	0.714	0.909	0.866	Valid and reliable

These results indicate that the indicators adequately represented their respective constructs. Therefore, the measurement model met the requirements for convergent validity and internal consistency reliability and was suitable for further evaluation of the structural model.

Discriminant validity was assessed using the Fornell-Larcker criterion. The square root of the Average Variance Extracted ($\sqrt{AVE}$) for each construct was compared with its correlations with the other constructs. As presented in Table 8, the diagonal value for learning engagement was 0.963, which exceeded its correlations with critical thinking skills (0.814) and scientific literacy (0.841). The diagonal value for critical thinking skills was 0.853, which was also greater than its correlations with learning engagement (0.814) and scientific literacy (0.792). Furthermore, the diagonal value for scientific literacy was 0.845, which exceeded its correlations with learning engagement (0.841) and critical thinking skills (0.792). These results indicate that the three constructs met the Fornell-Larcker criterion and demonstrated adequate discriminant validity.

Table 8. Fornell-Larcker criterion

Construct	Learning Engagement	Critical Thinking Skills	Scientific Literacy
Learning Engagement	0.963	-	-
Critical Thinking Skills	0.814	0.853	-
Scientific Literacy	0.841	0.792	0.845

Evaluation of the Structural Model

The structural model was evaluated using the coefficient of determination, path coefficients, and

bootstrapping results. The (R^2) value for critical thinking skills was 0.64, indicating that 64% of the variance in critical thinking skills was explained by the learning model and learning engagement. The (R^2) value for scientific literacy was 0.59, indicating that 59% of the variance in scientific literacy was explained by the variables in the model.

Table 9. Coefficient of determination

Endogenous Variable	R^2	Interpretation
Critical thinking skills	0.64	Moderate to strong
Scientific literacy	0.59	Moderate

The path coefficient analysis showed that the learning model had a strong positive and statistically significant effect on learning engagement ($\beta = 0.954$, $t = 158.441$, $p < 0.001$). This finding indicates that students who participated in AI-integrated Deep Learning Project-Based Learning demonstrated substantially higher learning engagement than students who received conventional instruction.

Learning engagement had a positive but non-significant effect on critical thinking skills ($\beta = 0.326$, $t = 1.823$, $p = 0.068$). In contrast, learning engagement had a positive and statistically significant effect on scientific literacy ($\beta = 0.827$, $t = 5.826$, $p < 0.001$).

The learning model also had a positive and statistically significant direct effect on critical thinking skills ($\beta = 0.511$, $t = 2.866$, $p = 0.004$). However, its direct effect on scientific literacy was not statistically significant ($\beta = 0.014$, $t = 0.095$, $p = 0.925$). These results indicate that the effect of the learning model on scientific literacy was primarily transmitted through learning engagement rather than through a direct pathway.

Table 10. Direct effects of the structural model

Hypothesised Relationship	Path Coefficient (β)	t-statistic	p-value	Decision
Learning model $\rightarrow$ Learning engagement	0.954	158.441	< 0.001	Supported
Learning engagement $\rightarrow$ Critical thinking skills	0.326	1.823	0.068	Not supported
Learning engagement $\rightarrow$ Scientific literacy	0.827	5.826	< 0.001	Supported
Learning model $\rightarrow$ Critical thinking skills	0.511	2.866	0.004	Supported
Learning model $\rightarrow$ Scientific literacy	0.014	0.095	0.925	Not supported

Mediation Analysis

The mediation analysis was conducted to determine whether learning engagement mediated the relationship between the learning model and students' critical thinking skills and scientific literacy. The indirect effect of the learning model on critical thinking skills through learning engagement was positive but not statistically significant ($\beta = 0.311$, $t = 1.834$, $p = 0.067$). The 95% bootstrap confidence interval included zero, indicating that learning engagement did not significantly mediate the relationship between the learning model and critical thinking skills.

In contrast, the indirect effect of the learning model on scientific literacy through learning engagement was positive and statistically significant ($\beta = 0.789$, $t = 5.875$, $p < 0.001$). Since the direct effect of the learning model on scientific literacy was not significant, while the indirect effect through learning engagement was significant, learning engagement was identified as an indirect-only mediator. This finding indicates that AI-integrated Deep Learning Project-Based Learning improved students' scientific literacy primarily by increasing their learning engagement.

Table 11. Indirect effects and mediation analysis

Indirect Relationship	Indirect Effect (β)	t-statistic	p-value	Mediation Decision
Learning model → Learning engagement → Critical thinking skills	0.311	1.834	0.067	No mediation
Learning model → Learning engagement → Scientific literacy	0.789	5.875	< 0.001	Indirect-only mediation

Discussion

Enhancing Critical Thinking Skills Through AI-Integrated Deep Learning Project-Based Learning

The findings of this study demonstrate that students who participated in AI-integrated Deep Learning Project-Based Learning achieved substantially higher critical thinking skills than students who received conventional instruction. This result can be explained by the structure of Project-Based Learning, which requires students to identify problems, analyse information, evaluate alternative solutions, develop evidence-based arguments, and communicate their conclusions. Chen & Yang (2021) reported that Project-Based Learning supports higher-order thinking because students are actively involved in meaningful and authentic tasks rather than passively receiving information. Similarly, Rehman et al. (2024a) found that project-based learning can strengthen twenty-first-century competencies by combining collaborative inquiry, problem-solving, and student engagement. In this study, the project activities provided direct opportunities for students to practise analysis, evaluation, inference, interpretation, and argumentation, which were the main indicators of critical thinking skills.

The direct effect of the learning model on critical thinking skills indicates that the instructional design itself played an important role in strengthening students' reasoning processes. The learning model required students to explore contextual science problems, examine evidence, justify their decisions, and revise their explanations throughout the project. These activities are consistent with the view that critical thinking develops when learners are repeatedly challenged to question assumptions, compare information, and construct defensible conclusions.

Salido et al. (2025) emphasised that the integration of critical thinking and artificial intelligence in higher education should focus on evaluation, verification, reasoning, and reflective judgment rather than on the passive acceptance of AI-generated answers. Walter (2024) similarly argued that AI literacy and prompt engineering should be connected with critical thinking so that students can assess the quality, relevance, and credibility of information produced by AI systems.

The role of AI in this study should not be interpreted merely as the use of digital tools, but as a cognitive partner that supported students during project investigation, conceptual exploration, and reflective evaluation. Through AI-assisted scaffolding, students were able to generate initial explanations, compare alternative scientific arguments, receive formative prompts, and revise the logic of their reasoning. Kasneci et al. (2023) noted that generative AI can support personalised feedback and exploratory learning, but its educational value depends on whether learners are required to verify, critique, and refine the generated information. This interpretation is also consistent with Simbolon & Silalahi (2023a), who showed that technology-supported inquiry learning can create opportunities for students to engage more actively with scientific concepts, and with Simbolon & Silalahi (2023b), who reported that virtual laboratory-based physics learning can improve students' learning activities.

The very large effect size for critical thinking skills ($d = 4.23$) indicates a substantial difference between the experimental and control groups. However, this result should be interpreted cautiously because such a large effect may reflect not only the strength of the intervention but also the contrast between the two

learning environments. While the control group received conventional instruction with fewer opportunities for inquiry, adaptive feedback, and reflective argumentation, the experimental group experienced a highly structured combination of projects, deep conceptual exploration, collaboration, and AI-supported feedback. Godsk & Møller (2025) emphasised that the effect of educational technology is strongly influenced by the extent to which it supports active learning, communication, interaction, and higher-level cognitive activities. Therefore, the magnitude of the effect in this study may partly reflect the limited capacity of conventional instruction to facilitate sustained critical reasoning rather than a universal effect that would necessarily occur in every instructional context.

Strengthening Scientific Literacy Among PGSD Students

The experimental group also achieved higher scientific literacy than the control group, indicating that AI-integrated Deep Learning Project-Based Learning supported students' ability to explain scientific phenomena, interpret data and evidence, evaluate scientific inquiry, and apply scientific knowledge in contextual situations. Scientific literacy requires more than memorising scientific concepts; it involves the ability to use scientific knowledge when analysing real-world issues and making evidence-based decisions. Al Sultan et al. (2021) emphasised that prospective elementary teachers need a comprehensive understanding of scientific literacy because their knowledge and beliefs will influence how they later teach science in primary classrooms. In the present study, contextual projects encouraged PGSD students to connect scientific concepts with authentic problems and to develop explanations that were meaningful beyond the classroom.

The improvement in scientific literacy can also be linked to the deep learning orientation embedded in the intervention. Students were not only asked to complete project products but were also guided to connect prior knowledge with new concepts, analyse evidence, reflect on their understanding, and transfer knowledge to new situations. Chen & Yang (2021) explained that project-based learning is most effective when projects are aligned with conceptual learning goals rather than treated merely as product-oriented activities. Rehman et al. (2024b) likewise showed that project-based learning can cultivate transferable competencies when students are actively involved in investigation, collaboration, and reflection. The combination of project activities and conceptual reflection may therefore have enabled students to develop a more integrated understanding of science.

The very large effect size for scientific literacy ($d = 4.04$) should also be interpreted in relation to the

different learning opportunities provided to the two groups. The experimental group received repeated opportunities to interpret information, compare scientific claims, discuss evidence, and receive feedback, whereas the control group had more limited exposure to these processes. The effect size may therefore indicate the cumulative influence of multiple instructional components rather than the isolated contribution of AI alone. Godsk & Møller (2025) cautioned that educational technology does not automatically improve learning outcomes; its benefits depend on how it is integrated into active learning and interaction. Similarly, Simbolon et al. (2022) found that Project-Based Learning supported by e-learning was effective when students were actively engaged in project planning, discussion, and task completion.

Learning Engagement as a Mediating Mechanism

The structural analysis showed that the learning model had a strong positive effect on learning engagement. This finding suggests that AI-integrated Deep Learning Project-Based Learning created a learning environment that encouraged behavioural participation, emotional involvement, and cognitive investment. Project ownership, group collaboration, contextual problems, and continuous feedback may have increased students' willingness to participate and persist in learning activities. Rehman et al. (2024a) identified student engagement as an important outcome of project-based learning because projects provide students with meaningful roles and opportunities to contribute actively. Godsk & Møller (2025) also demonstrated that educational technology can support behavioural, affective, and cognitive engagement when it is used to structure active learning, communication, and interaction.

Learning engagement did not significantly mediate the relationship between the learning model and critical thinking skills. This result indicates that the improvement in critical thinking skills was more directly associated with the cognitive demands of the learning model than with students' general level of engagement. The project tasks explicitly required analysis, evaluation, inference, interpretation, and argumentation, meaning that students practised critical thinking as an integral part of the instructional process. Salido et al. (2025) argued that critical thinking in AI-supported learning is strengthened when students are required to evaluate information, question outputs, and justify decisions. Kasneci et al. (2023) similarly noted that the benefits of generative AI depend on instructional designs that require active verification and reasoning rather than simple interaction with the technology.

In contrast, learning engagement significantly mediated the relationship between the learning model

and scientific literacy. The non-significant direct effect of the learning model on scientific literacy, combined with the significant indirect effect through engagement, indicates an indirect-only mediation mechanism. This means that the model improved scientific literacy primarily by encouraging students to participate actively, remain interested, invest cognitive effort, and persist in understanding scientific problems. Scientific literacy involves sustained engagement with data, evidence, inquiry processes, and contextual applications, making it reasonable that students' active involvement became an essential pathway for improvement. Al Sultan et al. (2021) highlighted the need for prospective teachers to engage deeply with the multiple dimensions of scientific literacy, while Godsk & Møller (2025) showed that technology-supported engagement is most effective when students are required to interact meaningfully with learning content.

The different mediation patterns for critical thinking skills and scientific literacy provide an important contribution to understanding how the intervention worked. Critical thinking skills appear to have been strengthened directly through the cognitive structure of the project tasks, whereas scientific literacy developed through the students' active engagement with scientific concepts and evidence. This finding suggests that engagement should not be treated as a universal mechanism that influences all learning outcomes in the same way. Rather, its role depends on the nature of the outcome being developed and the specific learning activities used. Rehman et al. (2024b) emphasised that project-based learning outcomes are shaped by the interaction between project design, student participation, and the competencies being targeted, while Walter (2024) noted that AI-supported learning must be designed according to clear pedagogical purposes.

Theoretical and Practical Implications for Teacher Education

Theoretically, this study supports the integration of Project-Based Learning, deep learning, AI-supported scaffolding, and student engagement within a single instructional framework. The findings indicate that the pedagogical structure of the model directly strengthened critical thinking skills, while its ability to stimulate engagement served as the main pathway for improving scientific literacy. This distinction extends previous research by showing that an integrated learning model may influence different learning outcomes through different mechanisms. Salido et al. (2025) emphasised that effective AI integration requires alignment between technology, pedagogy, and higher-order thinking, while Kasneci et al. (2023) argued that AI should be used to augment human reasoning rather than replace it.

Practically, teacher education programmes should design AI-supported learning activities that require prospective teachers to investigate authentic science problems, verify information, evaluate evidence, develop learning products, and reflect on their reasoning. AI should be used to provide guiding questions, formative feedback, alternative explanations, and self-assessment prompts, while lecturers remain responsible for monitoring the accuracy of scientific content and the quality of students' reasoning. Walter (2024) stressed that responsible AI use requires critical AI literacy, and Godsk & Møller (2025) showed that the engagement potential of technology depends on the educator's ability to integrate it into meaningful learning activities. The findings of Simbolon & Silalahi (2023a, 2023b) also support the use of technology-supported science learning to increase student activity and strengthen the learning process.

For PGSD programmes, the findings are particularly important because prospective elementary teachers need to develop both the ability to think critically and the capacity to teach science meaningfully. Scientific literacy among future teachers influences their readiness to explain scientific phenomena, guide inquiry, and help elementary students connect science with everyday life. Al Sultan et al. (2021) warned that limited understanding of scientific literacy may affect the ability of prospective teachers to respond to science education reforms. Therefore, AI-integrated Deep Learning Project-Based Learning can be considered a promising approach for preparing PGSD students to design student-centred, inquiry-oriented, and technology-supported science learning.

Despite the positive findings, the results should be interpreted within the limitations of the study. The very large effect sizes may have been influenced by the strong contrast between the experimental and conventional learning environments, the duration of the intervention, the novelty of AI-supported learning, and the alignment between the intervention activities and the assessment indicators. Godsk & Møller (2025) noted that technology-enhanced learning outcomes are highly dependent on context, implementation, and educator competence, while Kasneci et al. (2023) highlighted the need to examine both the opportunities and risks of generative AI in education. Future studies should therefore replicate the model across different institutions, use longer intervention periods, compare different AI tools, and examine whether improvements are sustained over time.

Conclusion

This study concludes that AI-integrated Deep Learning Project-Based Learning is an effective

instructional approach for improving the critical thinking skills and scientific literacy of Primary School Teacher Education students. Students in the experimental group achieved substantially higher post-test scores than those in the control group, with very large effect sizes for both outcomes. These findings indicate that the integration of authentic project activities, deep conceptual learning, and AI-supported feedback can create learning experiences that are more meaningful, inquiry-oriented, and cognitively demanding than conventional instruction. The structural model provides a more specific explanation of how the intervention influenced learning outcomes. The learning model had a significant direct effect on critical thinking skills, suggesting that activities involving problem analysis, evidence evaluation, argument construction, and reflective revision directly strengthened students' reasoning abilities. Learning engagement did not significantly mediate this relationship. In contrast, the effect of the learning model on scientific literacy occurred primarily through learning engagement. This indicates that behavioural participation, emotional involvement, and cognitive investment were important mechanisms in helping students explain scientific phenomena, interpret evidence, evaluate scientific inquiry, and apply scientific knowledge in contextual situations. These findings have important implications for PGSD programmes. Prospective elementary teachers need learning experiences that prepare them to design student-centred, inquiry-based, and technology-supported science instruction. AI should be positioned as a cognitive partner that provides scaffolding, formative feedback, alternative explanations, and reflective prompts, while students remain responsible for verifying information and constructing scientific arguments. This study was limited by its short intervention period, single institutional context, and self-reported engagement data. Future research should test the model across different universities, use longitudinal designs, compare different AI tools, incorporate observational measures of engagement, and examine the transfer of these competencies into actual elementary science teaching practice.

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Author Contributions

Conceptualization and methodology, writing-review and editing, D.H.S. and E.K.S.; formal analysis, E.K.S. and R.M.T.; investigation, visualization, D.H.S. and R.M.T.; writing-

preparation of initial draft, D.H.S. All authors have approved the published manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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