Jurnal Penelitian dan Pengkajian Ilmu Pendidikan: e-Saintika
https://journal-center.litpam.com/index.php/e-Saintika/index

March 2026 Vol. 10, No. 1
e-ISSN: 2615-6881
pp. 179-194

Analysis of the Effectiveness of Using AI-Generated Instructional Videos through Problem-Based Learning Model on Reconstruction of Fundamental Science Concepts

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Received: October 2025; Revised: December 2025; Published: March 2026

Abstract

The use of artificial intelligence (AI) has grown in elementary schools, but insufficient is known about the practical consequences of this technology, particularly as it pertains to the acquisition of scientific knowledge. Given that pre-service elementary teachers necessitate the cultivation of skills in intricate scientific ideas within problem-based learning (PBL) settings, there is an increasing demand for creative, technology-enhanced instructional resources. This study examines the influence of AI-generated instructional videos, created in accordance with recognized instructional design principles, on task performance, self-efficacy, and learning outcomes in pre-service elementary teachers. The present study utilized a within-subjects design with 186 participants, incorporating pretest, post-test, and transfer evaluations to measure the transferability and durability of learning. Substantial improvements were found from pre- to post-training, including a significant gain in self-efficacy ($t(185)=7.12$, $p<0.001$, $d=1.04$) and learning performance (e.g., immediate post-test $t(185)=8.45$, $p<0.001$). However, ANCOVA results indicated no significant advantage of the preview feature, such as in the delayed post-test ($F(1,184)=0.65$, $p=.42$) and transfer test ($F(1,184)=0.18$, $p=.67$). The results indicate that educational videos produced by artificial intelligence can substantially enhance knowledge transfer, retention, and self-efficacy, qualifying them as valuable resources for elementary teacher education in the field of elementary education.

Keywords: Instructional Video; Artificial Intelligence; Problem-Based Learning; Science Learning; Elementary School Teachers

How to Cite: Harefa, E., & Zega, N. A. (2026). Analysis of the Effectiveness of Using AI-Generated Instructional Videos through Problem-Based Learning Model on Reconstruction of Fundamental Science Concepts. *Jurnal Penelitian Dan Pengkajian Ilmu Pendidikan: E-Saintika*, *10*(1), 179-194. https://doi.org/10.36312/e-saintika.v10i1.3602

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INTRODUCTION

The technological advancement of education has altered the delivery, absorption, and application of knowledge (Haleem et al., 2022; Tan et al., 2025; Wang et al., 2024). The challenge in elementary teacher education in teaching science is in transmitting theoretical information and developing vital abilities, including critical thinking, collaborative problem-solving, and the capacity to convey complicated scientific concepts through engaging teaching methods (Alfarraj et al., 2023; Cortes et al., 2024). Problem-based learning (PBL) remains a significant pedagogical strategy due to its student-centered, inquiry-driven approach, which fosters meaningful engagement with real-world situations. PBL enables prospective elementary educators to engage directly with the dynamic relationship between practical problem-solving and scientific inquiry, establishing it as a fundamental component of excellent science teacher training (Harefa & Gulo, 2024; Koçoğlu & Kanadlı, 2025; Kwon et al., 2021).

Nonetheless, the transition to digital environments, propelled by technological progress and worldwide situations, has presented challenges in the efficient implementation of PBL. Ensuring student engagement, promoting learning in problem-solving contexts, and offering contextualized issue scenarios are substantial challenges in digital environments. Conventional instructional approaches sometimes fail to provide the engaging and immersive experiences essential for significant learning, especially for scientific subjects. This gap requires innovative strategies that leverage emerging technologies to revolutionize learning settings. Incorporating instructional videos within the PBL framework enriches learning by showcasing authentic, information-dense situations that promote engagement and critical thinking. Barman & Jena (2024) underscored the significance of interactive video anchors in establishing education via genuine problem-solving endeavors, including the examination of historical or environmental issues.

These instances underscore the significance of customizing video material to certain educational goals. Yaşar et al. (2024) illustrated the multimodal capabilities of video triggers in project-based learning, corresponding with contemporary students' interactive learning inclinations. Their investigation validated that video triggers enhance self-directed learning and collaborative inquiry when underpinned by adequate facilities and pedagogical coherence. Teacher educators can encourage independent and collaborative learning through technology-enhanced project-based learning, as Aidoo (2023) found. On the flip side, professional development is essential for improving video-based project-based learning environments due to challenges like time restrictions, resource shortages, and varying levels of educator competency. Research emphasizes the power of instructional videos in project-based learning settings, highlighting strategies like encouraging collaborative learning, selecting real-world material, overcoming obstacles to realization, and using narration to simplify difficult concepts and keep students' attention. A notable groundbreaking invention is the incorporation of artificial intelligence (AI)-generated videos for instruction into PBL settings.

These AI-generated videos, produced with sophisticated machine learning algorithms and natural language processing, may dynamically adjust to instructional requirements. It gives a visually engaging and interactive platform to illustrate intricate scientific concepts, replicate real-world situations, and offer structured assistance throughout problem-solving tasks. In contrast to static materials, AI-generated videos can be customised for certain educational environments, guaranteeing relevance and accessibility. For prospective scientific educators, such videos can function as instructional resources and exemplify how technology can augment education in the classroom. The incorporation of AI-generated instructional videos into project-based learning contexts presents revolutionary capability by enhancing learning experiences with personalised, interactive, and visually stimulating content. Utilising Large Language Models (LLMs), these videos enhance collaborative problem-solving and facilitate flexible scaffolding, rendering them very beneficial in elementary teacher education for teaching science.

Many educational settings are being made more accessible by generative AI technologies, which generate scalable, high-quality content by turning photos or slides into hyper-realistic videos. Studies by Pellas (2024) indicated that AI-generated videos yield results comparable to conventional recordings, exhibiting improved retention rates and successful facilitation of transfer assignments linked to self-efficacy. Furthermore, these technologies promote autonomy and self-directed learning, enabling prospective elementary teachers to study science and apply sophisticated approaches autonomously. An equitable strategy, wherein AI enhances human educators instead of supplanting them, maintains the relationship dimensions of education while optimizing AI's capabilities (Arkün-Kocadere & Özhan, 2024). AI-driven technologies in elementary teacher training increase material delivery and exemplify novel instructional techniques, promoting transdisciplinary interaction and equipping educators with future-ready teaching abilities. By harmonizing innovation with ethical considerations, AI-generated educational videos can revolutionize PBL environments and empower instructors with novel skills for teaching science (Bewersdorff et al., 2025).

The swift incorporation of AI in education has transformative prospects; nevertheless, its actual use in teacher training programs is still inadequately examined (Shahzad et al., 2025). Pre-service elementary teachers for teaching science necessitate new approaches to train educators for technology-enhanced classrooms and to equip them with the skills required to engage different learners. PBL environments provide effective frameworks for cultivating critical thinking, cooperation, and real-world problem-solving abilities (Pellas, 2024). The efficiency of AI-generated instructional videos in these contexts, especially regarding the enhancement of self-efficacy, learning outcomes, and task performance, for pre-service elementary teachers, remains not completely comprehended. PBL might encourage prospective science teachers to engage directly with the dynamic relationship between scientific inquiry and practical problem-solving, establishing it as a fundamental component of excellent elementary teacher training (Gumisirizah et al., 2024). The transition to digital environments, propelled by technical progress and global conditions, has complicated the proper implementation of PBL (Magaji et al., 2024). Consequently, there is a necessity for creative technologies and tactics that can efficiently facilitate PBL in digital contexts, especially in scientific teacher education.

Although prior studies explore the overall impact of AI-generated videos, no empirical work has isolated the effect of a preview or advance-organizer segment within AI-generated instructional videos (a feature theoretically tied to reducing cognitive load and supporting pre-training). Furthermore, evidence is lacking in PBL-based elementary teacher education, especially regarding combined retention and transfer outcomes, pre-service teachers learning Newtonian mechanics, and mixed designs comparing video features over multiple time points. Thus, the specific pedagogical value of the preview feature remains unclear in AI-generated science videos. This study offers three novel contributions in experimental comparison of preview and no-preview segments in AI-generated science videos, mixed-design analysis across four time points (pre-test, post-test, delayed post-test, transfer), and integration of AI-generated media in a PBL environment. This study delves into the effectiveness of educational videos created by AI in addressing these issues. To enhance student engagement in online project-based learning activities, AI-generated videos can provide visually appealing and contextually enhanced scenarios.

The objective of this study was to i) evaluate the effectiveness of AI-generated instructional videos in improving pre-service teachers' self-efficacy and conceptual understanding; ii) compare the effects of preview and no-preview versions on immediate learning, retention, and transfer, and iii) examine whether the preview feature improves performance beyond the base benefits of AI-generated videos in a problem-based learning (PBL) setting. Based on the objectives of this study, the following research hypotheses were raised: H1-Participants will show significant improvements from pre-test to post-test, delayed post-test, and transfer; and H2-Participants viewing the preview version will outperform those in the no-preview condition. This does double duty: it deepens our understanding of AI's role in the classroom and offers concrete ways to better prepare elementary school teachers to teach science, while also giving teachers access to the innovative possibilities of AI-generated instructional videos that can meet the challenges of today's classrooms.

METHOD

Research Design

The type of research used was quantitative research with a within-subjects/ repeated measures design with all participants experiencing all given conditions, as this study investigated the comparative effectiveness of instructional videos created by AI with and without preview features on learning outcomes, self-efficacy, and knowledge transferability. The study integrated AI-generated learning videos into PBL for teaching science to prospective elementary teachers by utilizing the (Interpret, Design, Evaluate, Articulate (IDEA) framework, with a detailed description shown in Figure 1.

	Interpret	*Design*	*Evaluate*	*Articulate*
Phase I: Observing and Explaining Natural Phenomena	Participants are guided to interpret and understand natural phenomena by observing and analyzing scientific events.	Participants collaborate with AI tools to develop a detailed observation plan.	Participants critically analyze their observation data based on Newton's principles.	Participants present their interpretations and reasoning to peers through presentations or reports.
Phase II: Conducting Experiments and Analyzing Results	Participants are introduced to experimental scenarios, such as testing the effect of mass on acceleration or analyzing forces on an inclined plane.	Using AI, each participant designs an experimental workflow, including hypothesis, variables, and data collection methods.	Participants evaluate their experimental results by comparing their findings with the expected outcomes derived from Newton's laws.	Participants articulate their experimental findings through interactive presentations, supported by AI-generated visuals like graphs, tables, and infographics.
Phase III: Advanced PBL in Science Learning	The lead researcher introduces complex scientific challenges, such as designing a water filtration system or analyzing pendulum dynamics.	Participants design solutions using AI-generated tools to build and refine prototypes or simulate outcomes.	Participants test their solutions using AI-based simulations and evaluate the results.	Participants present their problem-solving process and results to peers and instructors, supported by AI-generated explanatory content.
Phase IV: Interactive Features and Technical Considerations	The lead researcher guides participants to understand the importance of using digital tools for effective learning.	Participants design their learning schedules and practices around these interactive features.	Participants reflect on the benefits of interactive features in improving their understanding and memory of Newton's laws.	Participants articulate their experiences with interactive features through written or oral feedback, supported by AI prompts.

Figure 1. IDEA framework.

Research Procedures

Researchers used the Standards Self-Efficacy Scale (SSES) developed by Shaukat et al. (2024) to examine the self-efficacy of prospective elementary education students in learning science concepts. The instrument consisted of pre-self-efficacy and post-self-efficacy questionnaires and was selected because of its strong internal consistency. Each item was rated on a Likert scale, and the instrument was examined for validity and reliability. The scale was used to measure participants' confidence before and after watching an AI-generated instructional video on Newton's laws.

To determine participants' initial level of self-efficacy, the pre-self-efficacy questionnaire was administered before the instructional video was developed and presented. This study also responded to the need for practical evaluation of instructional media design principles by assessing the effectiveness of science learning objectives through pre-tests, post-tests, and transfer assessments, which were intended to measure both the durability and transferability of learning (Lin et al., 2025).

Participants completed a sequence of tests and learning conditions focused on one science topic, namely Newton's laws of motion. First, they took a pre-test consisting of multiple-choice and essay questions designed to assess their foundational knowledge. One example asked, "Which of Newton's laws explains why a moving object continues in motion unless acted upon by an external force?" At the same stage, participants completed the pre-self-efficacy questionnaire (PrSSES), which included seven items adapted from the original SSES to measure perceived problem-solving self-efficacy. The PrSSES showed strong reliability, with a Cronbach's alpha of 0.84.

The intervention required each participant to watch two versions of an AI-generated instructional video on Newtonian mechanics. In the preview condition, participants watched a version that began with a 20–30 second advance organizer presenting the learning objectives, emphasizing the key Newtonian concepts, and outlining the structure of the video through simple signaling cues. In the no-preview condition, participants watched an otherwise identical video that began directly with the instructional explanation and did not include an introductory organizer. Both videos were produced using AI tools on the Sudowrite, Visla, and Jasper platforms, as shown in Figure 2. All participants completed both video conditions in a counterbalanced within-subjects design, as illustrated in Figure 3.

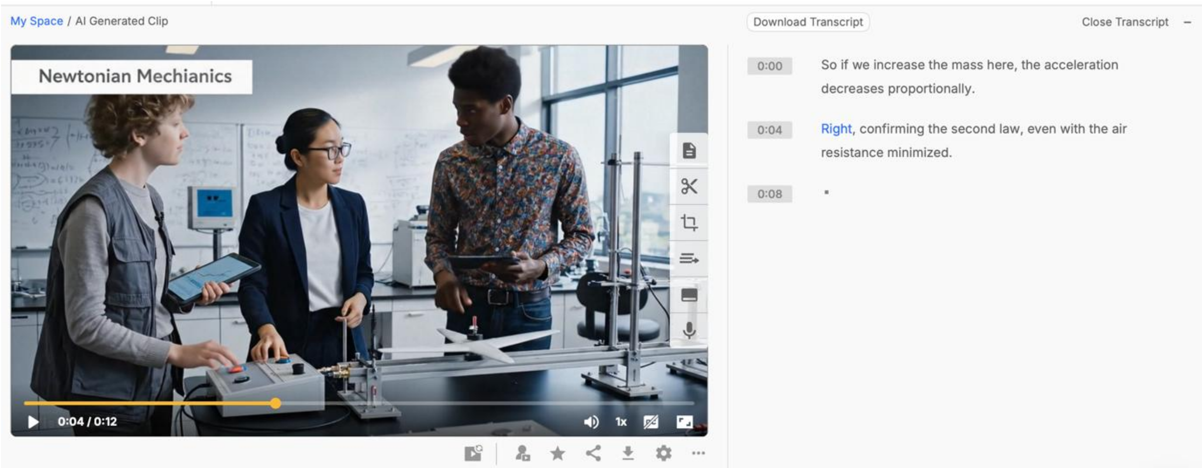

Figure 2. Participants created AI-generated videos for Newtonian mechanics topic

After completing both video conditions, participants took an immediate post-test to assess their comprehension and application of the concepts presented in the videos. They also completed the post-self-efficacy questionnaire (PsSSES), which demonstrated strong reliability with a Cronbach's alpha of 0.82. Seven days after the intervention, participants completed a delayed post-test to evaluate retention of the material over time. Immediately afterward, they completed a transfer test that measured their ability to apply the learned concepts to new situations through a problem-based learning task involving roller coaster design.

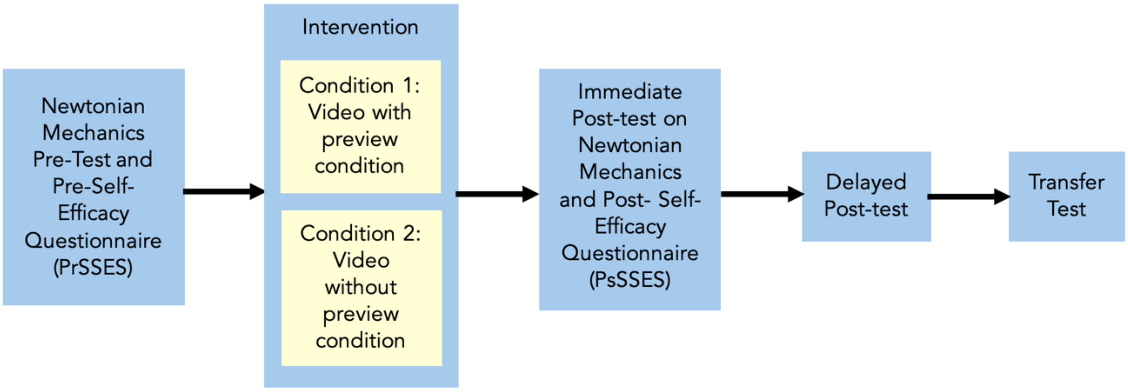

Figure 3. Flowchart of the research design

Research Participants

A total of 186 elementary school teacher education students of Universitas Nias taking the Fundamental Concepts of Science course were involved in this study, with 89 males (47.85%) and 97 females (52.15%), with a mean age of 18.49 (SD=0.46; range: 18-20). The participants were selected using a purposive sampling technique, considering that they were familiar with the use of AI and instructional technology. Pre-service elementary teachers were selected because they were enrolled in the Fundamental Concepts of Science course, represented the target group for PBL-based science instruction, and possessed basic digital literacy needed to engage with AI-generated videos. Participants were included if they were officially registered in the course, had prior familiarity with digital learning tools, could complete all stages of the intervention, and provided informed consent. This consideration-based sampling ensured that all participants had comparable academic backgrounds and were suitable for evaluating the instructional impact of AI-generated learning materials.

Data Collection and Data Analysis

Data were gathered via structured assignments designed in accordance with the instructional videos created by AI. The exercises evaluated participants' capacity to comprehend and implement the topics demonstrated in the videos. Each assignment was evaluated for precision, receiving zero points for inaccurate or incomplete submissions and full points for accurate completion. Data analysis was conducted utilizing IBM SPSS 27.0. Initial equivalency was evaluated utilizing Chi-square tests (for gender distribution) and independent-sample t-tests (for age, PrSSES, and pre-test scores). Paired-sample t-tests were employed to assess the impact of the tutorial on test performance and self-efficacy at different time intervals. ANCOVA was conducted to assess the impact of condition, incorporating pre-test self-efficacy and pre-test scores on Newtonian mechanics as factors, with prior verification of homogeneity of variance. The significance level was established at α = 0.05, with effect sizes evaluated in accordance with Cohen's criteria (small: d = 0.2, medium: d = 0.5, large: d = 0.8) (Cortina, 1993).

Ethical Considerations

This study received approval from ethics committee of Universitas Nias, and all procedures adhered to established research ethics standards. Participants were informed about the purpose of the study, the voluntary nature of their involvement, and their right to withdraw at any time without penalty. Written informed consent was obtained prior to data collection. All responses were kept confidential and anonymized, with data used solely for research purposes. No physical, psychological, or academic risks were posed to participants, and the instructional materials used in the study aligned with their regular coursework.

RESULTS AND DISCUSSION

Baseline Equivalence and Sequence Effects

Under both conditions, the PrSSES scores were essentially equivalent at baseline. Participants in the video-without-preview condition had a mean PrSSES score of 5.93 (SD = 1.02), whereas participants in the video-with-preview condition had a mean score of 5.88 (SD = 1.19), $t(185) = 0.72$, $p = 0.47$. This result indicates that participants entered the intervention with comparable levels of self-efficacy across conditions.

In contrast, pre-test scores differed significantly between the two counterbalanced sequences, indicating an order effect. Participants who first viewed the video without preview obtained a higher mean pre-test score (M = 0.56, SD = 0.20) than those who first viewed the video with preview (M = 0.47, SD = 0.21), $t(184) = 3.28$, $p < 0.001$. To account for this baseline difference, pre-test scores were included as a covariate in all ANCOVA models. This adjustment confirms that the non-significant effects of the preview feature were not attributable to pre-existing differences between the sequences.

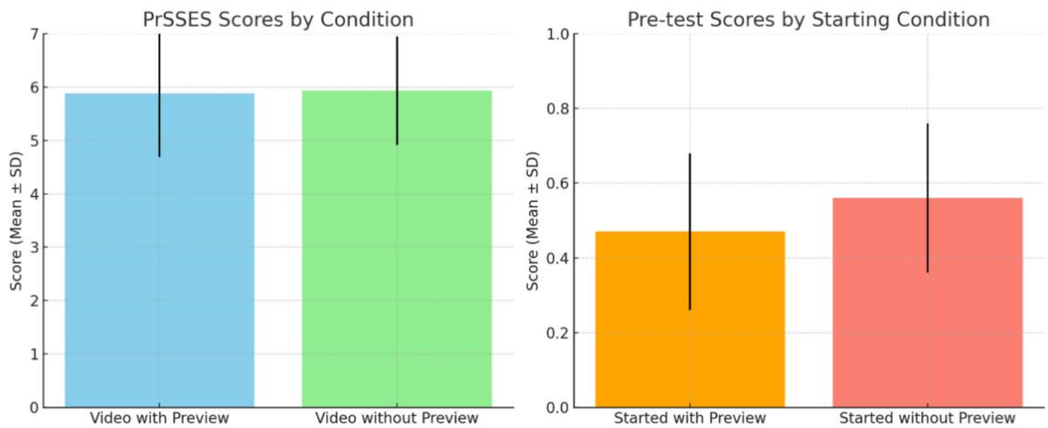

Figure 4. The PrSSES and Pre-test and scores by condition

The difference in baseline pre-test performance suggests that the first assigned task may have influenced participants' initial performance across contexts. Figure 4 presents the pre-test scores for the video-with-preview and video-without-preview conditions, with error bars representing standard deviations. The same figure also displays PrSSES scores for both conditions, again with error bars to illustrate variability.

Changes in Self-Efficacy After the Intervention

Participants' self-efficacy increased significantly following the training, as shown in Figure 5. Across 186 participants, post-training self-efficacy scores ($M = 6.72$, $SD = 0.68$) were higher than pre-training scores ($M = 5.81$, $SD = 1.15$). A paired-samples t-test confirmed that this increase was statistically significant, $t(185) = 7.12$, $p < 0.001$. The effect size was large (Cohen's $d = 1.04$), indicating a practically meaningful impact of the intervention. These findings support the hypothesis that the video tutorial enhanced participants' self-efficacy.

Participants' initial self-efficacy was already relatively high, with a mean of 5.81, which was above the midpoint of the scale. This suggests that most participants initially perceived the science learning tasks as manageable. Even so, the intervention produced a substantial additional increase, highlighting its value in strengthening participants' confidence. However, comparisons between the video-with-preview and video-without-preview conditions showed no statistically significant difference in self-efficacy. A post-hoc power analysis conducted in G*Power, using $\alpha = 0.05$, an observed effect size of Cohen's $d = 0.14$, and a sample of 186 participants, yielded low statistical power (0.34). Therefore, although the intervention improved self-efficacy overall, the non-significant effect of the preview feature should be interpreted cautiously because the study may have been underpowered to detect small differences between conditions.

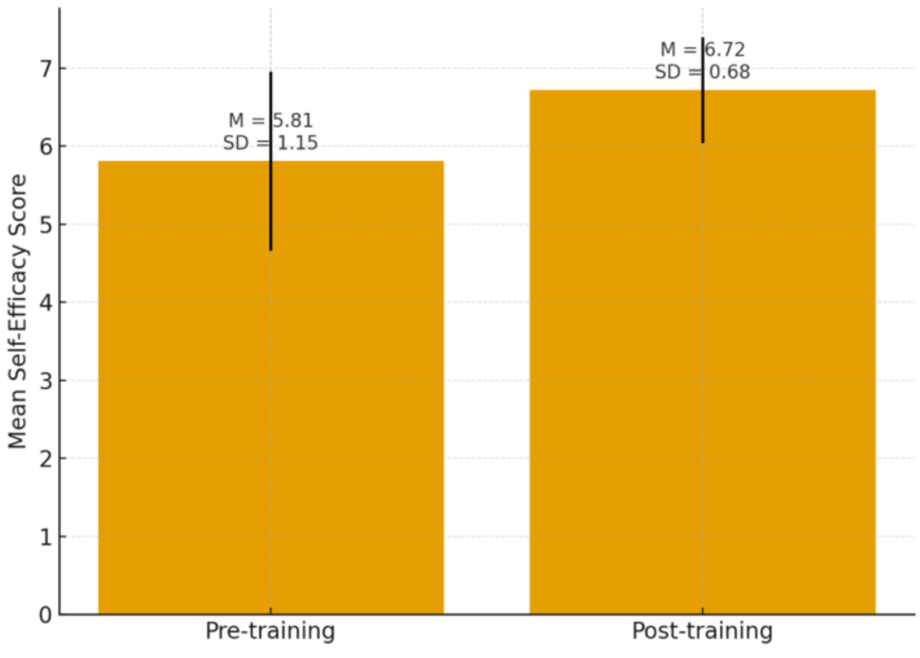

Figure 5. Self-efficacy results during the pre-training and post-training

Overall Learning Outcomes Across Assessments

Figure 6 shows performance across the four assessments: pre-test, immediate post-test, delayed post-test, and transfer test. Participants obtained the highest scores on the delayed post-test ($M = 0.78$, $SD = 0.30$), indicating strong retention of the instructional content over time. The lowest scores were recorded on the pre-test ($M = 0.43$, $SD = 0.20$), showing substantial room for improvement before the intervention. Immediate post-test scores increased markedly from baseline ($M = 0.69$, $SD = 0.26$), and transfer-test performance also remained high ($M = 0.73$, $SD = 0.28$), suggesting that participants were able to apply the learned concepts to novel situations.

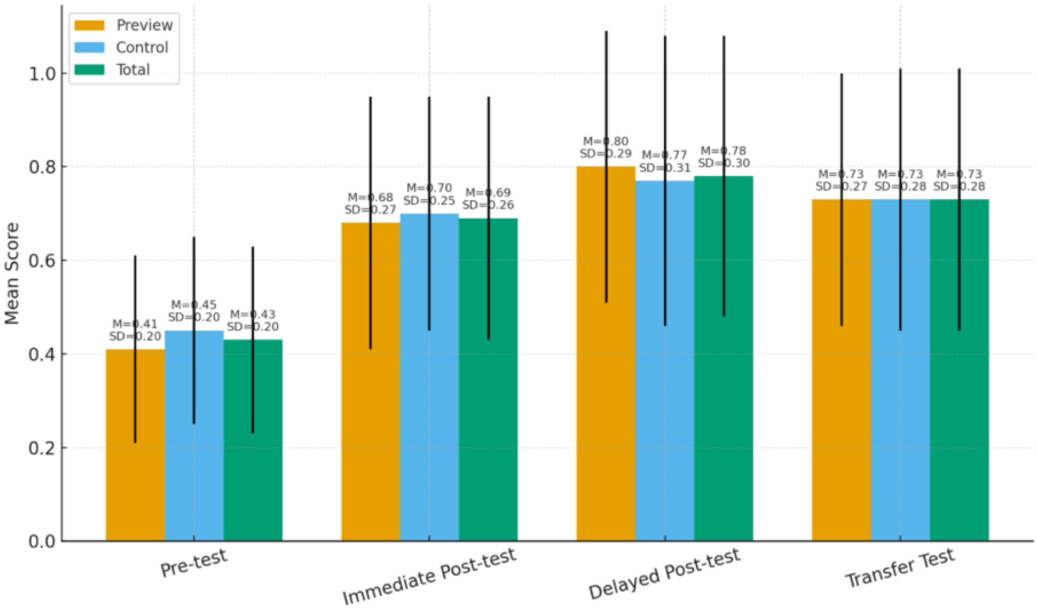

Figure 6. The PrSSES and Pre-test and scores by condition

As shown in Figure 7, one-sided paired-samples t-tests confirmed significant gains across all follow-up assessments compared with the pre-test. Immediate post-test scores (M = 0.69, SD = 0.26) were significantly higher than pre-test scores (M = 0.43, SD = 0.20), t(185) = 8.45, p < 0.001, d = 0.78, indicating a moderate-to-large effect. Delayed post-test scores (M = 0.78, SD = 0.30) were also significantly higher than pre-test scores, t(185) = 12.10, p < 0.001, d = 1.21, showing a large effect and strong retention over time. Likewise, transfer-test scores (M = 0.73, SD = 0.28) exceeded pre-test scores, t(185) = 6.55, p < 0.001, d = 0.61, indicating a moderate effect and demonstrating that participants were able to apply newly learned concepts in unfamiliar contexts. Collectively, these findings show that the AI-generated video lesson improved participants' performance across all post-intervention assessments.

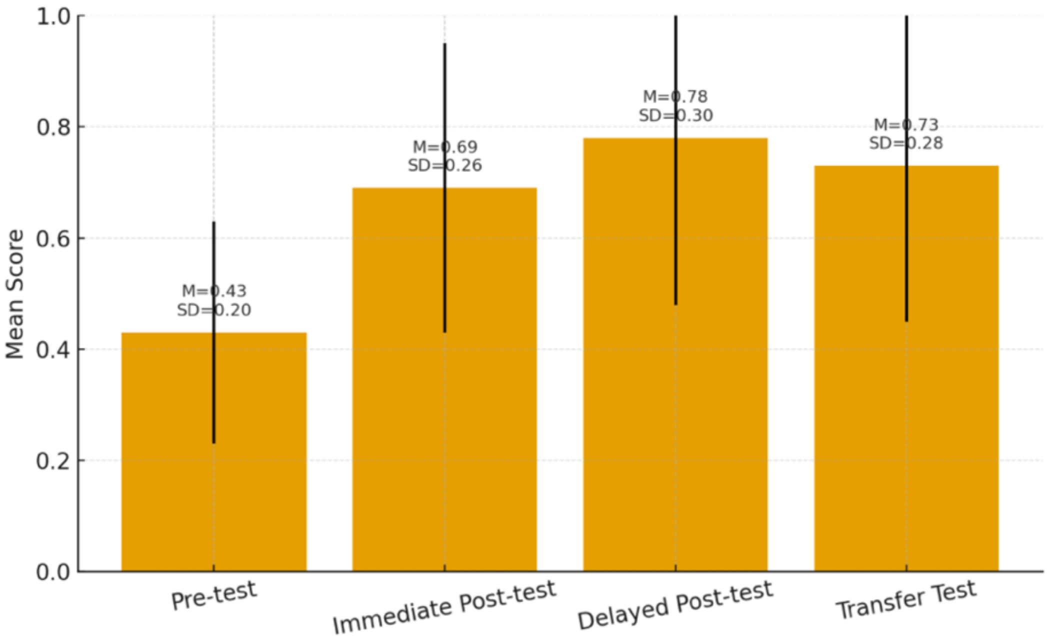

Figure 7. Overall task performance across tests

Effect of the Preview Feature on Task Performance

An ANCOVA was conducted to evaluate the effect of condition while controlling for pre-test scores, as shown in Table 1. No violations of the homogeneity of variance assumption were detected across the tests. The analysis showed that the preview condition did not significantly improve performance relative to the video-without-preview condition on the immediate post-test, $F(1, 184) = 0.42$, $p = 0.52$. Similarly, no significant condition effect was observed on the delayed post-test, $F(1, 184) = 0.65$, $p = 0.42$, or on the transfer test, $F(1, 184) = 0.18$, $p = 0.67$. Although the preview condition showed slightly higher average scores on some measures, these differences were not statistically significant. Overall, the results indicate that the preview feature did not significantly improve task performance on the immediate, delayed, or transfer assessments.

Table 1. ANCOVA results for overall task performance across tests

Outcome Measure	Source	SS	df	MS	F	p	Partial η^2
Immediate Post-test	Corrected Model	1.73	2	0.87	7.61	0.001	0.08
	Intercept	52.14	1	52.14	455.51	<0.001	0.71
	Pre-test (Covariate)	0.84	1	0.84	7.36	0.007	0.04
	Condition	0.05	1	0.05	0.42	0.52	0.00
	Error	20.99	184	0.11	—	—	—
	Total	75.42	187	—	—	—	—
	Corrected Total	22.72	186	—	—	—	—
Delayed Post-test	Corrected Model	1.17	2	0.58	5.24	0.006	0.05
	Intercept	19.64	1	19.64	175.36	<0.001	0.48
	Pre-test (Covariate)	1.10	1	1.10	9.85	0.002	0.05
	Condition	0.07	1	0.07	0.65	0.42	0.004
	Error	20.57	184	0.11	—	—	—
	Total	41.38	187	—	—	—	—
	Corrected Total	21.74	186	—	—	—	—
Transfer Test	Corrected Model	0.67	2	0.33	3.03	0.05	0.03
	Intercept	18.97	1	18.97	170.80	<0.001	0.48
	Pre-test (Covariate)	0.65	1	0.65	5.41	0.02	0.02
	Condition	0.02	1	0.02	0.18	0.67	0.001
	Error	20.45	184	0.11	—	—	—
	Total	40.15	187	—	—	—	—
	Corrected Total	21.12	186	—	—	—	—

Across all three tests, the partial η^2 values for the condition effect (preview vs. no preview) were extremely small, ranging from .001 to .004. These values indicate that the preview feature explained less than 1% of the variance in performance after adjustment for pre-test scores. According to conventional benchmarks, these effects fall below the threshold for a small effect. This pattern confirms that the preview segment did not meaningfully contribute to learning performance beyond the instructional content of the AI-generated videos themselves (see Figure 8).

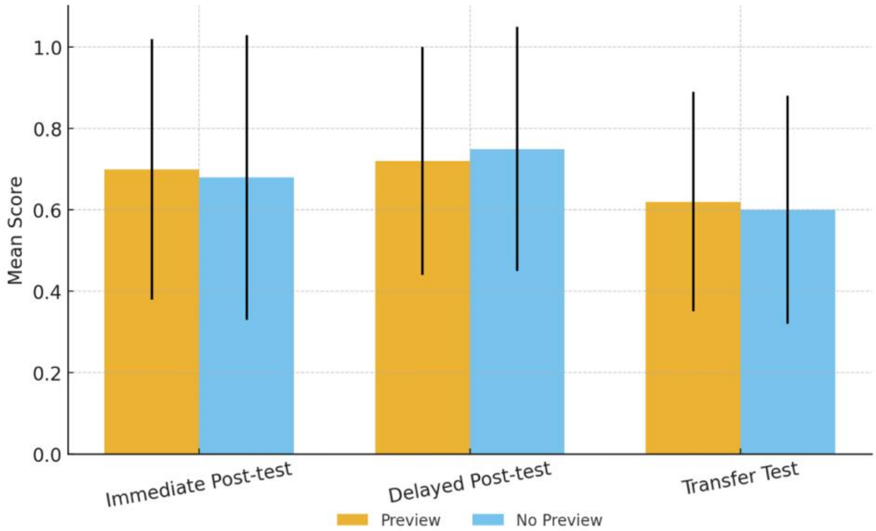

Figure 8. Overall task performance across tests

Discussion

Improvement in Learning Performance After the AI-Generated Video Intervention

The purpose of this study was to examine whether preview content embedded in AI-generated instructional videos used in project-based learning could improve pre-service primary school teachers' self-efficacy, retention, and task performance in science learning. The results show that participants' performance improved substantially from the pre-test to the immediate post-test, delayed post-test, and transfer test. The delayed post-test yielded the highest mean score ($M = 0.78$), suggesting not only immediate learning gains but also strong retention over time. These findings indicate that AI-generated instructional videos can support conceptual understanding and sustained learning in Newtonian mechanics.

This pattern is consistent with Arkün-Kocadere and Özhan (2024), who also reported meaningful gains in learning performance after multimedia-based instruction. The increase from the pre-test ($M = 0.43$) to later assessments suggests that AI-generated videos offered an engaging and accessible means of presenting new content, thereby supporting the effectiveness of multimedia learning (Gumisirizah et al., 2024).

Why the Preview Feature Did Not Produce Additional Benefits

Despite the overall improvement in learning outcomes, the addition of a preview segment did not yield a significant advantage over the no-preview condition. Several theoretical explanations may account for this result. First, a ceiling effect may have occurred (Staus et al., 2021). Because participants achieved relatively high delayed post-test scores, the main instructional content may already have been sufficiently clear and informative, leaving little room for the preview to generate measurable additional benefits.

Second, the preview may have been too brief or too general to function effectively as an advance organizer. According to Mayer's Pre-training Principle and Signaling Principle (La Torre & Désiron, 2024; Mayer, 2021), previews are most effective when they identify essential concepts, clarify structural relationships, and reduce extraneous cognitive load. In the present study, the preview may not have provided enough conceptual scaffolding to alter learners' processing in a meaningful way.

Third, participants' prior knowledge may have moderated the effect of the preview. Cognitive Load Theory suggests that supports such as advance organizers are particularly beneficial for novice learners (Gkintoni et al., 2025; Zhu et al., 2024). However, participants in this study had already encountered foundational science concepts in their coursework and demonstrated moderate pre-test performance. As a result, the preview may not have introduced sufficiently new cues to reduce cognitive load or enhance understanding beyond what participants already knew.

Finally, the project-based learning context itself may have reduced the necessity of a preview segment. Because participants engaged in inquiry, discussion, and problem-solving activities, relevant prior knowledge may already have been activated before they watched the videos. In this context, the instructional value of the preview may have overlapped with the preparatory function already provided by the learning environment.

Implications for Self-Efficacy Development

A major contribution of this study is the finding that the AI-generated instructional videos substantially improved participants' self-efficacy. The increase from pre-training to post-training scores suggests that the intervention strengthened participants' confidence in learning science and completing related tasks. This result is important because self-efficacy is closely associated with persistence, engagement, and willingness to tackle challenging learning activities.

The finding aligns with previous studies showing that multimedia instructional tools can improve learners' perceived competence and motivation (Li et al., 2024; Shahzad et al., 2025). Although the preview feature did not produce a separate effect, the video tutorials themselves appear to have played an important role in increasing self-confidence. Therefore, the educational value of AI-generated videos in this study lies more in their overall instructional support than in the added preview component.

Practical Implications

The present results indicate that AI-generated instructional videos were effective in improving performance and self-efficacy, but the preview feature did not significantly enhance these outcomes. This finding is broadly consistent with prior work reporting that preview-based or signaling-related supports do not always produce measurable gains under all conditions (Al-Zahrani & Alasmari, 2024). Although the preview was designed to provide context and reduce cognitive load in line with the IDEA framework (Lin et al., 2025), its practical contribution was not evident in the observed learning outcomes.

From a practical perspective, these findings suggest that the core quality of the instructional video may be more important than adding a brief preview segment. For teacher education and science instruction, well-designed AI-generated videos may already provide sufficient conceptual support to improve understanding, retention, transfer, and self-efficacy. Future studies should examine whether longer, more explicit, or more interactive preview segments produce stronger effects, especially for learners with lower prior knowledge or in topics that involve greater conceptual complexity.

CONCLUSION

The objective in doing this study is to bridge the gap between the theoretical possibilities and practical applications of AI-generated instructional video tutorials in teaching science. The purpose of these discoveries is to lay the groundwork for new approaches to education that integrate AI-generated videos into PBL settings; this should help aspiring pre-service elementary teachers learn more effectively and be better prepared for teaching science. This study enhances the ongoing discourse on the transformative impact of technology on education, enabling educators to motivate the forthcoming generation of critical thinkers and scientists. Consistent with the study's objectives and hypotheses, the findings demonstrate that AI-generated instructional videos are an effective learning resource: they enhanced learners' self-efficacy, conceptual understanding, retention, and transfer, aligning with emerging evidence that AI-mediated materials can perform comparably to traditionally produced instructional media. However, the results did not support the hypothesis that a preview segment contributes additional value. Instead, the findings directly address the research gap by showing that, within AI-generated videos, previews may not function as effective advance organizers in this context. Possible explanations include ceiling effects, the adequacy of the main instructional content, and the pre-existing activation of prior knowledge through PBL activities

The present research intends to improve the digital competency of pre-service elementary teachers by providing practical experience in creating and evaluating instructional videos using AI. These results suggest that design efforts should prioritize core instructional quality rather than supplemental preview elements, specifically emphasize conceptual clarity, integrate videos purposefully into PBL cycles, incorporate active processing opportunities, and maintain consistency in visual design and signaling. As AI-generated media becomes more prevalent, responsible implementation is essential. Teacher educators should ensure transparency regarding the use of AI tools in content creation, protect learner data privacy, and critically evaluate the accuracy, bias, and appropriateness of AI-generated materials. Encouraging pre-service teachers to reflect on these considerations supports informed and ethical adoption of AI technologies in their future classrooms. Overall, the study indicates that AI-generated instructional videos can effectively support science learning in PBL environments, even without preview segments. The focus, therefore, should be on high-quality core content, purposeful pedagogical integration, and ethically guided use of AI, rather than relying on brief previews to enhance learning outcomes.

RECOMMENDATION

While this study does shed light on the effectiveness of AI-generated educational videos for teacher training, there are still many unanswered questions. The effectiveness of previews that are both interactive and adaptive, including features like short quizzes or material that is adapted to each learner's needs, should be the subject of future studies. Learners' interactions with the preview function can be better understood using eye-tracking approaches.

Acknowledgment

The authors would like to thank Directorate of Research and Community Service (DPPM), Ministry of Higher Education, Science, and Technology (Kemendiktisaintek) of the Republic of Indonesia. In addition, the author would like to thank LDDIKTI Wilayah I and LPPM of Universitas Nias for providing support in carrying out this research.

Funding Information

This research was funded by Directorate of Research and Community Service (DPPM), Ministry of Higher Education, Science, and Technology (Kemendiktisaintek) of the Republic of Indonesia for funding this research through Penelitian Dosen Pemula (PDP) research scheme (Research contract: 122/C3/DT.05.00/PL/2025, 40/SPK/LL1/AL.04.03/PL/2025, 096/UN01/PN.02.11/2025).

Conflict of Interest Statement

Authors state no conflict of interest.

Data Availability

Data availability is not applicable to this article because no new data were created or analyzed in this study.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Edward Harefa	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓
N. Andriani Zega	✓	✓			✓	✓			✓	✓		✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

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