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Adaptive Deep Learning–Driven Animated Media for Enhancing Science Concept Understanding in Elementary Education

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ABSTRACT

Elementary science instruction in the digital era often lacks interactivity and responsiveness to diverse learning needs, particularly for abstract topics such as the water cycle. This study examines the effect of adaptive animated media supported by deep learning features on Grade 4 students' conceptual understanding and compares it with conventional instruction. A quasi-experimental nonrandomized control-group pretest–posttest design was employed with 50 fourth-grade students at SDN Sukarahayu 02 (25 experimental; 25 control). Both groups completed a 20-item multiple-choice pretest and posttest, while the experimental group also responded to a perception questionnaire. The experimental group used adaptive animated modules featuring progress monitoring, branching reinforcement, differentiated practice, and targeted feedback, whereas the control group received lecture-based instruction with textbooks and worksheets. Data were analyzed using normalized gain scores and the Mann–Whitney test. Initial abilities were comparable (experimental = 52.35; control = 51.80). Posttest scores were higher in the experimental group (82.75) than in the control group (68.45). Learning gains were greater in the experimental group (g = 0.638, medium) compared to the control group (g = 0.345, medium). The difference was statistically significant (p = 0.012). Student perceptions indicated increased engagement (88%), improved understanding (84%), enhanced visualization (88%), and higher motivation (80%). Adaptive animated media effectively supports conceptual understanding by providing personalized learning pathways and visualizing abstract processes, leading to more meaningful learning experiences than conventional methods. Deep learning–supported adaptive animation significantly enhances elementary students' understanding of the water cycle and offers a more interactive and effective alternative to traditional instruction.

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1. INTRODUCTION

The Fourth Industrial Revolution is reshaping education by requiring schools to respond quickly to technological change and increasingly diverse student needs. Digital learning is moving beyond conventional delivery toward more immersive, collaborative, and data-informed approaches, making instructional innovation a necessity rather than an option (Bryda & Costa, 2023; Mhlongo et al., 2023; Mierlo & Beers, 2020; Salazar, 2023). In this context, Artificial Intelligence (AI) is often positioned as a strategy to improve learning quality by helping teachers provide learning experiences that are more relevant and aligned with learner needs (Salem, 2024). Among AI approaches, deep learning is rapidly developing because it can detect patterns in learner data and support personalization such as adaptive difficulty, targeted feedback, and tailored learning activities (Kanchon et al., 2024; Murtaza et al., 2022).

However, elementary students' understanding of science concepts remains a persistent problem. Initial observations at SDN Sukarahayu 02 indicated that 60% of upper-grade students did not reach the Minimum Mastery Criterion (KKM) of 75, suggesting that students' conceptual processing is not yet well supported and learning outcomes are still uneven. One contributing factor is that science instruction remains relatively teacher-centered: students are frequently directed to complete tasks rather than guided to explore, reason, and construct concepts through meaningful inquiry (Alguacil et al., 2024). Learning activities can become procedural, with limited space for explanation and reflection after tasks are finished (Wieselmann et al., 2019). This is particularly problematic in science because many topics involve abstract or invisible processes that require visualization, simulation, and concrete representations to help students build accurate mental models. Yet, learning media that specifically visualizes scientific processes—such as well-designed animation—has not been widely used in classroom practice.

Another challenge is that instruction often lacks adaptivity. Students differ in readiness and learning preferences, but they typically receive the same materials and pacing. This may cause slower learners to fall behind and faster learners to be under-challenged (El-Sabagh, 2021; Morze et al., 2021). When instruction does not respond to these differences, learning tends to become superficial: students memorize rather than understand and struggle to transfer knowledge to new situations. Because science understanding in the early years underpins later critical thinking and scientific literacy, addressing this issue is important. These conditions reveal a clear research gap. While prior studies frequently discuss digital innovation and the value of visual media, relatively few studies integrate animation with AI-driven adaptivity in a technically explicit manner and test it empirically in elementary classrooms. In particular, research remains limited on instructional media that simultaneously (1) visualizes abstract science processes through animation and (2) uses a trained deep learning model to personalize learning paths and feedback using student interaction patterns. This study addresses that gap by developing and evaluating deep learning–based animated media for elementary science, focusing on the water cycle, using a quasi-experimental design.

To meet this need, the study proposes deep learning–based adaptive animation. Animation is selected because it can make abstract ideas more concrete through motion-based visualization, simulation, and narrative support, helping students form clearer mental models of scientific phenomena (Skulmowski, 2024; Skulmowski & Xu, 2022). To avoid one-way delivery, deep learning is incorporated so the media can adapt to students rather than presenting a single fixed pathway. Here, "deep learning–based media" is used in a technical sense: the system incorporates a trained deep neural network that processes interaction data—such as quiz responses, time-on-task, error patterns, and revisited sections—to estimate mastery and recommend the next learning step (Gao, 2025; Y. Lin et al., 2025). The mastery profile is then linked to adaptive branching: students who show misconceptions are routed to additional explanatory animations, scaffolded prompts, and tiered practice, while students who demonstrate mastery proceed to more challenging tasks or enrichment. Through this mechanism, the media is expected to provide more individualized support and help reduce learning gaps across students (Fatchurahman et al., 2022; Utaminingsih et al., 2024).

The approach is supported by theoretical and empirical considerations. For elementary learners, concrete representation is essential, and animated visualization can reduce cognitive load by externalizing processes that are difficult to imagine and clarifying cause–effect relationships through dynamic depiction. Empirical evidence also indicates that animation can strengthen science concept understanding by making abstract ideas more accessible (Mou, 2023; Strømme & Mork, 2021). In addition, motion-graphic learning resources have been associated with improved outcomes and motivation, which can support attention and retention (Hanif, 2020). From an instructional perspective, adaptive learning aligns with differentiated instruction, which emphasizes matching learning experiences to students' readiness and profiles. Deep learning methods can operationalize this principle through data-driven personalization and feedback (Kanchon et al., 2024; Murtaza et al., 2022). Although Cao & Huang (2025) highlight deep learning's potential to improve learning quality, the application of deep learning–enabled adaptivity within animated science media for elementary classrooms remains insufficiently developed. Related work in technology-enhanced learning further suggests that personalization is most effective when it is grounded in learner data and implemented through continuous feedback loops (Barut et al., 2022; Qushem et al., 2021).

In terms of positioning, this study aligns with prior work emphasizing visual and interactive technologies to support learning, especially for abstract content (Annetta et al., 2024; Kuznetcova et al., 2025). However, it differs in focus and contribution. Annetta et al. (2024) emphasize scientific literacy through spatial computing, whereas this study targets science concept understanding through adaptive animated media tested experimentally. Kuznetcova et al. (2025) focuses on civic learning via low-tech immersive storytelling and participatory design, while this study evaluates adaptive animation for science learning through quantitative outcomes and student perceptions. Matovu et al, (2023) report mixed results in immersive VR research; in contrast, this study tests a classroom-oriented adaptive animation model and links learning outcomes to specific adaptive features, including progress monitoring, branching support, targeted feedback, and AI-assisted scaffolding.

Based on this gap, the study aims to analyze the impact of integrating deep learning–based animated media on elementary students' understanding of science concepts. It examines whether science learning can be made both visually comprehensible and responsive to individual needs, and whether this improves conceptual understanding compared with conventional instruction. The novelty lies in developing animated science media that is not only interactive and visual but also adaptive through a trained deep learning model that supports personalized learning routes and feedback (Gao, 2025; Y. Lin et al., 2025). Practically, the study is expected to inform teachers in designing media for process-oriented science topics that require visualization (Skulmowski, 2024; Skulmowski & Xu, 2022). Theoretically, it contributes to the emerging discourse on embedding deep learning into elementary instructional media through explicit learner modeling and adaptive branching, supporting broader learning transformation in the digital era (Salazar, 2023; Salem, 2024).

2. METHODS

This study used a quasi-experimental method with a Nonrandomized Control-Group Pretest–Posttest Design (Cresswell, 2009). The population comprised all fourth-grade students at SDN Sukarahayu 02 in the 2024/2025 academic year (N=50). The sample consisted of 25 students from class IV A (experimental group) and 25 students from class IV B (control group). The sample was selected using purposive sampling, with the consideration that the two classes had relatively homogeneous characteristics and were therefore comparable.

2.1 Ethical consideration

This study adheres to ethical research principles for educational settings (Cohen et al., 2017). Formal approval was obtained from the principal of SDN Sukarahayu 02. Informed consent was secured from the parents or guardians of all student participants prior to the study, in accordance with standard ethical guidelines (APA, 2017), detailing the research purpose, procedures, and their rights. Student assent was also verbally obtained at the beginning of each activity.

2.2 Intervention and procedure

The intervention was implemented in eight sessions over four weeks, and each session lasted 70 minutes (one standard lesson period). The learning topics followed the fourth-grade science curriculum, including the water cycle, energy, and the solar system. In the experimental group, students used the Deep Learning-based animation media on individual tablets. Each session was structured as follows: (a) adaptive animation introduction (15 minutes), (b) interactive AI-paced exercises and simulations (35 minutes), and (c) guided discussion and reflection (20 minutes). The adaptivity feature of the media was implemented by adjusting visual complexity and quiz difficulty based on students' real-time responses during use. In the control group, students learned the same topics through conventional instruction (teacher lectures, textbook reading, and static image-based worksheets) with the same time allocation. Pretests were administered one week before the intervention, and posttests were conducted one week after the final session.

2.3 Instruments, validity, and reliability

Three instruments were used. The learning outcome test (science concept understanding) consisted of a 20-item multiple-choice test covering cognitive levels C1–C4. Content validity was established through expert judgment (two science education specialists and one evaluation expert), resulting in an Aiken's V value of 0.85. Reliability was tested using the Kuder–Richardson 20 (KR-20) on a pilot sample (n = 30), yielding a coefficient of 0.82 (Kuder & Richardson, 1937). The student perception questionnaire comprised 15 Likert-scale items (1 = Strongly Disagree to 4 = Strongly Agree) measuring engagement, ease of understanding, and motivation. Construct validity was reviewed by two educational technology experts, and reliability (Cronbach's alpha) was 0.88 (Cronbach, 1951). An observation sheet was used to document students' engagement during learning activities, including attention, participation, and interaction with the media/tools.

2.4 Data analysis and gain calculation

Quantitative data were analyzed using the Kolmogorov–Smirnov test for normality, Levene's test for homogeneity, and the Mann–Whitney test (SPSS 25.0) to examine differences in science learning outcomes between the experimental and control groups. To address the reviewers' comment regarding N-Gain, the improvement score reported in this study was a gain score calculated using the formula:

$$< g > = \frac{(post\ test\ scores) - (pre\ test\ score)}{(maximum\ score) - \ (pre\ test\ score)}$$

The obtained N-gain scores were categorized according to the following criteria (Hake, 1999):

Table 1. N-gain Categories Categories

Category	N-gain
High	(g) ≥ 0.70
Medium	0.30 ≤ (g) < 0.70
Low	(g) < 0.30

3. FINDINGS AND DISCUSSION

3.1 Finding

Students' baseline ability was first measured using a pretest administered to both groups. The experimental group then learned using deep learning–based animated media, while the control group received conventional instruction. After the intervention, a post-test was administered to measure improvement in science concept understanding, and a perception questionnaire was distributed to capture students' responses to the media. The descriptive results are presented in Table 2.

Table 2. Pre-test and Post-test Results of the Experimental and Control Groups

Group	Test	Mean	Std. Deviasi	Minimum Score	Maximum Score	Posttest-Pretest difference	N-Gain
Experimental	Pretest	52.35	7.89	40	65	30.40	0.638
	Posttest	82.75	6.45	70	95		
Control	Pretest	51.80	6.95	45	65	16.65	0.345
	Posttest	68.45	7.12	55	80		

The two groups started from comparable pretest performance, but the experimental group showed greater improvement on the posttest and a higher normalized gain (medium category) than the control group.

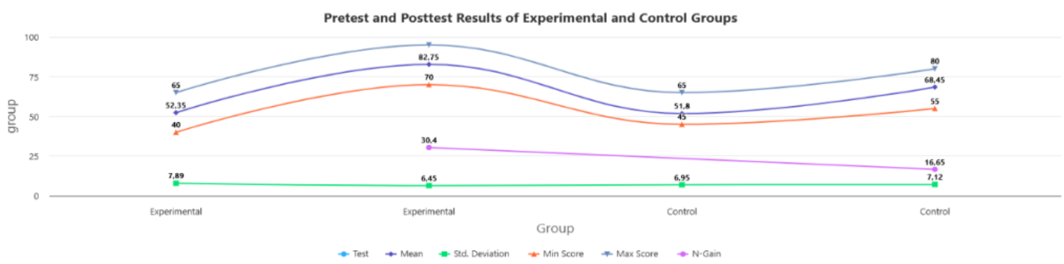

Figure 1. Comparison of Mean Pre-test and Post-test Scores

To visualize the difference, Figure 1 plots the mean pre-test and post-test scores for both groups. The experimental group shows a larger increase from pre-test to post-test than the control group, indicating stronger improvement after the animated media intervention.

Table 3. Statistical Test Results

Statistical Test	Significance	Decision
Kolmogorov–Smirnov (Experimental)	0.072	Data are normally distributed
Kolmogorov–Smirnov (Control)	0.085	Data are normally distributed
Levene's Test	0.21	Variances are homogeneous
Mann-Whitney Test	0.012	H_0 rejected

The hypothesis test with Mann–Whitney U on posttest scores showed a significant difference between groups ($U = 183.00$, $Z = 2.51$, $p = 0.012$). This result indicates the rejection of H_0 and acceptance of H_a, meaning there is a significant difference between the learning outcomes of the experimental and control groups. The effect size was calculated using $r = Z/\sqrt{N}$ (Fritz et al., 2012), yielding $r = 0.36$, which represents a medium-to-large effect according to Cronbach's (1951) conventions ($r = 0.10$ small, 0.30 medium, 0.50 large). In addition to investigating gains in science concept understanding, students' responses to the media were also examined with a perception questionnaire (Table 4).

Table 4. Student Perception Questionnaire Results on Deep Learning–Based Animated Media

Statement	Agree	Total	Percentage (%)
The media makes learning more engaging	22	25	88
The material is easier to understand	21	25	84
The media helps visualize abstract concepts	22	25	88
The media motivates students to learn more actively	20	25	80

Overall, students reported positive responses, indicating that the media supported engagement, clarity of material, visualization of abstract concepts, and motivation.

Figure 1. Deep Learning–Based Animated Media

The media provides a sequenced module menu, animated visualization, and interactive controls (including progress tracking and an AI support feature) to guide students through the water cycle topic. The implementation of this media in classroom learning activities is shown in Figure 3.

Figure 2. Classroom Learning Activities Using Deep Learning–Based Animated Media

Students used laptops to access the media during learning, while the teacher facilitated and monitored activities, supporting a more active and guided learning process.

3.2 Discussion

3.2.1 Interpretation of the Findings for Students' Science Concept Understanding

The findings indicate that the use of deep learning based animated media in elementary science instruction significantly benefits students' science concept understanding in the Water Cycle topic. Both groups began with relatively comparable baseline performance (mean pretest: experimental = 52.35; control = 51.80), so the learning gains after instruction can be attributed more confidently to differences in treatment. After the intervention, the experimental group achieved a higher mean posttest score (82.75) than the control group (68.45), producing a 14.30 point difference. This pattern is also reflected in learning gains, where the experimental group showed a higher N Gain (30.40 points; g = 0,638) than the control group (16.65 points; g = 0,345). These results suggest that the media supported deeper conceptual understanding rather than simple recall, likely because animation and interactivity help students build clearer mental models of abstract processes such as cloud formation, rainfall, and surface runoff, and reduce misconceptions through dynamic representations that can be observed and explored. This aligns with evidence from a network meta analysis in science education showing that interactive learning environments such as augmented reality, mixed reality, and interactive digital games generally have stronger potential to improve cognitive and affective outcomes than conventional teaching by promoting multisensory engagement and active participation (Koç & Kanadlı, 2025).

The advantage of the media is further supported by the posttest hypothesis test (Mann Whitney), which produced a significance value of 0.012 ($p < 0.05$). This indicates a statistically significant difference between groups and suggests that the animated media does more than enrich visual presentation. It improves science concept understanding more effectively than predominantly conventional instruction by combining interactivity, feedback, and more structured learning support (Halkiopoulos & Gkintoni, 2024; Shemshack & Spector, 2020). Students' perceptions were also positive, with 84 percent reporting that the material was easier to understand and 80 percent reporting greater motivation to learn actively. This is consistent with research showing that animation based or interactive video materials can sustain motivation without excessively increasing cognitive load, although interactivity must still be designed carefully to avoid adding unnecessary cognitive burden for some learners (Tugtekin & Dursun, 2022).

Regarding claims about deep learning adaptivity, this study shows that the media includes features that support self-paced learning and learner control, such as a sequential module structure, simulation controls, and Quick Facts that allow students to revisit sections they have not yet understood. However, if the study does not report technical evidence that the system performs AI-driven personalization, such as system logs or adaptivity metrics, then claims about deep learning-based adaptivity should be interpreted as feature-level adaptivity and student self-regulation rather than validated model-based personalization. Therefore, evidence from systematic reviews on AI adaptive learning can be used as a conceptual foundation, but the empirical claim should be limited to the media's ability to facilitate pacing, repetition, and independent exploration unless future work provides model level or log based indicators of personalization (C. C. Lin et al., 2023; Xaveria & Kristianingsih, 2025).

3.2.2 Connections to Prior Studies in Students' Science Concept Understanding

These findings reinforce literature highlighting the value of visual and interactive instruction for improving conceptual learning. Prior studies suggest that visual representations and interactive experiences can strengthen understanding and retention, particularly in science literacy and concept vocabulary development (Annetta et al., 2024), and that interactivity can increase psychological immersion that supports learner engagement (Kuznetcova et al., 2025). The contribution of this study is more focused because it provides direct empirical evidence through a quasi-experimental design with a control group, supported by quantitative data and student perception data. In this way, the study goes beyond general claims that technology increases motivation by showing more consistent cognitive gains on a process-based topic. This addresses prior observations that in immersive technology supported science learning, engagement gains do not always translate into improved cognitive outcomes (Matovu et al., 2023). In this context, the combination of process visualization, instructional interactivity, and learning support features such as staged modules, simulation controls, progress monitoring, and embedded assistance likely contributed to more stable learning improvement.

3.2.3 Implications for Elementary Science Teaching and School Implementation

Practically, the results suggest that deep learning-based animated media deserves serious consideration as an instructional innovation in elementary science, especially for topics that are process-oriented and difficult to visualize. Teachers can integrate the media as a complement to instruction to help students understand natural phenomena through dynamic representations while supporting differentiated learning through simulation controls, staged modules, and progress indicators. From a school and policy perspective, the findings highlight the need for an enabling implementation ecosystem that includes teacher training in digital pedagogy, adequate devices and access, and responsible guidance for AI related features, including learner data protection and transparency about how the system functions. Academically, the study opens opportunities for further research to examine long term retention, effectiveness across other science topics, and more detailed evaluation of adaptive components so that media design can become more targeted and scalable for elementary school contexts.

3.2.4 Research Limitations

The findings should be interpreted in light of several limitations. First, the sample size is limited and comes from only one school, so generalization to broader contexts should be made cautiously. Second, the intervention period was relatively short, so the study cannot confirm long term retention or sustained conceptual change. Third, the scope was limited to the Water Cycle topic, so effectiveness for other science topics remains to be tested. Fourth, the study does not report technical constraints or operational evidence, such as usage logs or adaptivity metrics, that would verify AI-driven personalization. Therefore, any claims about deep learning-based personalization should be framed carefully or strengthened in future studies through clearer documentation of system mechanisms and reporting of adaptivity indicators derived from user interaction data

4. CONCLUSION

This study shows that adaptive animated media supported by deep learning–inspired features can improve Grade 4 students' science concept understanding in the water cycle unit. Both groups started with comparable baseline performance (experimental pretest mean = 52.35; control pretest mean = 51.80). After the intervention, the experimental group achieved a higher posttest mean (82.75) than the control group (68.45), indicating stronger improvement. The normalized gain was higher in the experimental group ($g = 0.638$, medium) than in the control group ($g = 0.345$, medium), confirming that learning progress was more substantial when students learned with the animated media. The Mann–Whitney test on posttest scores indicated a statistically significant difference between groups ($p = 0.012$), with an effect size of $r = 0.36$, suggesting a meaningful educational impact. Students also reported positive perceptions of the media, with most indicating that learning became more engaging (88%), easier to understand (84%), helpful for visualizing abstract processes (88%), and more motivating (80%), which has practical implications for teachers to use the media as a structured complement for concept introduction, guided exploration, and reinforcement with feedback, especially for abstract and dynamic topics; at the policy level, scaling this approach requires minimum device-readiness support, teacher professional development in digital pedagogy and data-informed instruction, and clear governance of learner data (privacy, transparency, and responsible use); for future AI-based media design, developers should refine adaptive features with interpretable progress indicators, misconception-aligned feedback, adjustable scaffolding, and evidence that personalization decisions are measurable and linked to learning outcomes; accordingly, future research should test long-term retention using posttests, expand samples across diverse schools to assess generalizability and equity, and add learning-process instruments (interaction patterns, help-seeking, metacognitive indicators, and cognitive load) to explain mechanisms of impact more comprehensively.

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