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The Impact of Adaptive Learning Based on Artificial Intelligence on Elementary School Students' Mathematics Learning Motivation

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Abstract: This research aims to examine the effect of artificial intelligence-based adaptive learning on elementary school students' mathematics learning motivation. This research is quantitative research with the type of experimental research. The experimental design used was a quasi experiment involving class 4a students at SD Negeri Cileungsir as the experimental class (30 students) and class 4b students at SD Negeri Cileungsir as the control class (30 students). This research data is quantitative data collected using questionnaire techniques. The collected data was then analyzed using descriptive statistical test techniques by testing individual acquisition values and classical averages. Individual and classical scores are then interpreted based on the categorization table. Next, the data were analyzed using inferential statistical test techniques using independent t-tests and paired t-tests. The research results show that adaptive learning based on artificial intelligence has a positive and significant effect on elementary school students' mathematics learning motivation. This is evident from research data which shows that there was a significant increase in the average score of students' mathematics learning motivation in the experimental class between before and after being given treatment, namely from 62.34 (low category) to 90.78 (very high category). Furthermore, the average posttest score for students' mathematics learning motivation in the experimental class showed 90.78 (very high category), while in the control class it was 67.12 (low category). This means that the mathematics learning motivation of students who use artificial intelligence-based adaptive learning is better. Inferential statistical tests were carried out in this study to test the research hypothesis. The results of the prerequisite tests are used as a basis for continuing hypothesis testing using parametric statistical techniques using the t-test type. The results of the independent t-test and paired t-test show that the significance value is smaller than the alpha value, namely 0.000 (<0.005). Based on these results, adaptive learning based on artificial intelligence can be used as an alternative to overcome the low motivation to learn mathematics in elementary school students.

Keywords: Adaptive learning, artificial intelligence, mathematics learning motivation.

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INTRODUCTION

Mathematics occupies a central position in elementary education because it provides the foundational competencies required for logical reasoning, problem solving, quantitative literacy, and decision-making in everyday life. The development of mathematical competence at the elementary level has been consistently recognized as a critical determinant of students' future academic achievement and lifelong learning trajectories. However, the effectiveness of mathematics education is not determined solely by cognitive factors. A substantial body of research has demonstrated that students' motivation to learn mathematics significantly influences engagement, persistence, self-regulation, and achievement outcomes (Ryan & Deci, 2020; Schukajlow et al., 2022). Consequently, increasing students' motivation toward mathematics learning has become a major concern for educators, researchers, and policymakers worldwide.

Learning motivation refers to the internal and external forces that initiate, direct, and sustain learning behaviors toward achieving educational goals. Motivated students tend to display greater attention, effort, perseverance, and willingness to overcome academic challenges than students with low motivation (Eccles & Wigfield, 2020). In mathematics education, motivation is particularly important because many learners perceive mathematics as a difficult and abstract subject. Such perceptions often contribute to mathematics anxiety, reduced engagement, and declining academic performance, especially during the elementary school years when foundational attitudes toward mathematics are being established (Foley et al., 2017; Luttenberger et al., 2018).

Numerous international assessments have highlighted persistent concerns regarding students' mathematics learning outcomes and attitudes toward mathematics. Reports from the Programme for International Student Assessment (PISA) indicate that many students continue to demonstrate low confidence and limited enthusiasm in mathematics learning despite ongoing educational reforms (OECD, 2023). Similar challenges have been observed in developing countries, including Indonesia, where mathematics achievement remains closely associated with motivational factors, learning environments, and instructional quality (Kemendikbudristek, 2022).

At the elementary school level, mathematics instruction frequently relies on conventional teaching approaches characterized by uniform learning materials, teacher-centered instruction, and limited personalization. Such practices often fail to accommodate differences in students' prior knowledge, learning pace, cognitive readiness, and learning preferences. Consequently, students with varying abilities receive similar learning experiences regardless of their individual needs, potentially reducing engagement and learning motivation (Tomlinson, 2017). Educational researchers have increasingly argued that personalized learning environments are necessary to address learner diversity and promote meaningful learning experiences.

The emergence of digital technologies has created new opportunities to transform traditional instructional practices into more learner-centered approaches. Among these innovations, adaptive learning has gained considerable attention because of its capacity to provide personalized learning experiences based on individual learner characteristics and performance. Adaptive learning systems dynamically adjust learning content, instructional pathways, feedback, and task difficulty according to students' progress and learning needs (Holmes et al., 2019). Such personalization enables students to learn at an appropriate pace while receiving targeted support throughout the learning process.

Recent advances in artificial intelligence (AI) have significantly enhanced the capabilities of adaptive learning systems. Artificial intelligence enables educational platforms to analyze large amounts of learner data, identify patterns in student performance, predict learning difficulties, and generate personalized instructional recommendations in real time (Zawacki-Richter et al., 2019). Through machine learning algorithms and intelligent analytics, AI-based adaptive learning environments can continuously refine learning experiences to maximize student engagement and learning effectiveness.

The integration of artificial intelligence into educational settings has attracted increasing scholarly attention during the past decade. Researchers have reported that AI technologies can support personalized learning, formative assessment, intelligent tutoring, and learner analytics across diverse educational contexts (Chen et al., 2020; Ouyang & Jiao, 2021). In elementary education, AI applications have shown promising potential for enhancing students' learning experiences by providing individualized guidance and adaptive instructional support that would be difficult to achieve through conventional classroom practices alone.

The theoretical foundations supporting AI-based adaptive learning can be traced to constructivist learning theory and self-determination theory. Constructivist perspectives emphasize that learners actively construct knowledge through interactions with learning experiences tailored to their developmental needs (Piaget, 1972; Vygotsky, 1978). Meanwhile, self-determination theory suggests that learning motivation increases when learners experience autonomy, competence, and relatedness within educational environments (Ryan & Deci, 2020). AI-based adaptive learning systems can potentially satisfy these psychological needs by offering personalized learning pathways, appropriate challenges, and immediate feedback.

Immediate and personalized feedback constitutes one of the most important features of adaptive learning environments. Feedback allows learners to identify mistakes, monitor progress, and improve understanding. Research has shown that timely feedback contributes significantly to learner motivation because it enhances students' perceptions of competence and achievement (Hattie & Timperley, 2007; Wisniewski et al., 2020). AI technologies facilitate continuous feedback mechanisms that can be delivered instantly based on individual student responses.

Another advantage of AI-based adaptive learning lies in its ability to accommodate diverse learner characteristics. Elementary school classrooms typically consist of students with varying levels of mathematical proficiency, learning readiness, and motivational orientations. Traditional instruction often struggles to address such diversity effectively. Adaptive learning systems, however, can personalize learning activities and difficulty levels according to each learner's profile, thereby reducing frustration among struggling learners while maintaining challenges for advanced learners (Kulik & Fletcher, 2016).

Several empirical studies have reported positive relationships between adaptive learning technologies and student engagement. For instance, adaptive digital learning environments have been found to increase students' active participation, task persistence, and learning satisfaction across different educational levels (Walkington & Bernacki, 2020). Enhanced engagement is particularly relevant because engagement functions as a key mediator between instructional interventions and learning motivation.

In mathematics education, AI-supported learning environments have demonstrated considerable potential for improving both cognitive and affective outcomes. Studies indicate that intelligent tutoring systems and adaptive mathematics platforms can improve mathematical understanding, problem-solving skills, and learner confidence (Ma et al., 2021; Bond et al., 2024). These findings suggest that AI-based interventions may contribute not only to academic performance but also to students' motivational development.

Despite growing interest in AI applications in education, research focusing specifically on elementary school students' mathematics learning motivation remains relatively limited. Existing studies frequently emphasize academic achievement, learning outcomes, or technological acceptance while paying less attention to motivational dimensions. Given that motivation serves as a critical precursor to sustained learning and achievement, further investigation is necessary to understand how AI-based adaptive learning influences motivational processes among young learners (Sailer & Homner, 2020).

The Indonesian educational context presents a particularly relevant setting for examining this issue. In recent years, the Indonesian government has actively promoted digital transformation in education through initiatives emphasizing technology integration, digital literacy, and innovative learning approaches. Nevertheless, challenges related to student motivation and mathematics learning outcomes continue to persist in many elementary schools (Kemendikbudristek, 2022). Therefore, identifying effective technology-enhanced instructional strategies capable of improving motivation represents an important educational priority.

Preliminary observations conducted at SD Negeri Cileungsir revealed several issues associated with students' mathematics learning motivation. Many students demonstrated limited enthusiasm during mathematics lessons, low participation in classroom discussions, reluctance to solve mathematical problems independently, and insufficient persistence when encountering challenging tasks. Teachers also reported considerable variation in students' learning abilities, making it difficult to provide individualized instruction within conventional classroom settings.

These classroom conditions indicate a mismatch between students' diverse learning needs and the instructional approaches commonly employed during mathematics lessons. When students consistently encounter learning experiences that fail to correspond with their readiness levels and interests, their motivation may gradually decline. Consequently, innovative instructional approaches capable of providing personalized learning experiences are required to address this challenge effectively.

Artificial intelligence-based adaptive learning offers a promising solution because it enables learning experiences to be adjusted continuously according to students' performance and progress. By presenting learning materials at appropriate levels of difficulty, providing individualized feedback, and supporting self-paced learning, adaptive learning environments may foster greater learner autonomy and competence. These characteristics align closely with theoretical determinants of learning motivation identified in contemporary educational psychology literature (Ryan & Deci, 2020; Eccles & Wigfield, 2020).

Furthermore, AI-based adaptive learning may contribute to reducing mathematics anxiety among elementary school students. When learners receive tasks that correspond to their current abilities and obtain supportive feedback throughout the learning process, they are less likely to experience repeated failure and frustration. Reduced anxiety can subsequently promote more positive attitudes toward mathematics and strengthen students' willingness to engage in learning activities (Luttenberger et al., 2018).

The increasing availability of educational technologies and AI-powered learning platforms has generated substantial expectations regarding their potential educational benefits. However, evidence-based evaluations remain essential because the effectiveness of technological innovations depends largely on how they are implemented within specific educational contexts. Educational researchers have therefore emphasized the importance of conducting rigorous experimental studies to examine the actual impacts of AI-based learning interventions on student outcomes (Holmes & Tuomi, 2022).

A review of previous literature reveals several research gaps. First, many studies have focused on secondary or higher education settings, leaving elementary education relatively underexplored. Second, investigations frequently prioritize cognitive outcomes rather than motivational variables. Third, empirical evidence from Indonesian elementary schools remains limited despite increasing interest in educational AI applications. These gaps indicate the need for further research examining the influence of AI-based adaptive learning on mathematics learning motivation among elementary school students.

Based on these considerations, this study investigates the impact of artificial intelligence-based adaptive learning on elementary school students' mathematics learning motivation through a quasi-experimental design involving experimental and control groups. The study seeks to provide empirical evidence regarding whether AI-supported adaptive learning can significantly enhance students' motivation toward mathematics learning. The findings are expected to contribute to the growing body of literature on artificial intelligence in education while offering practical implications for teachers, schools, and policymakers seeking effective strategies to improve mathematics learning motivation in elementary education.

METHODS

Research Design

This study employed a quantitative approach using a quasi-experimental research design to examine the effect of artificial intelligence-based adaptive learning on elementary school students' mathematics learning motivation. Quantitative experimental methods were selected because they provide a rigorous framework for identifying causal relationships between independent and dependent variables through systematic comparison of treatment and control groups (Creswell & Creswell, 2018; Fraenkel et al., 2019). The independent variable in this study was artificial intelligence-based adaptive learning, while the dependent variable was students' mathematics learning motivation.

The quasi-experimental method was considered appropriate because the existing classroom structure in elementary schools did not allow for random assignment of students into experimental conditions. Consequently, intact classes were used as research groups while maintaining comparable learning conditions across classes. The study utilized a nonequivalent control group design consisting of pretest and posttest measurements administered to both experimental and control groups. This design enabled the researchers to evaluate changes in students' mathematics learning motivation before and after the intervention while simultaneously controlling for initial differences between groups (Shadish et al., 2002).

The experimental group received mathematics instruction through an artificial intelligence-based adaptive learning platform, whereas the control group received mathematics instruction through conventional teacher-centered approaches commonly implemented in the school. Both groups studied the same mathematical topics, followed the same curriculum standards, and received instruction within the same academic period. The intervention was implemented over eight consecutive weeks to ensure that students had sufficient exposure to the adaptive learning environment and to allow meaningful changes in learning motivation to emerge.

The research design incorporated pre-intervention and post-intervention measurements to assess motivational changes over time. The pretest was administered before the intervention to establish baseline equivalence between groups, while the posttest was administered after completion of the instructional treatment. The comparison of pretest and posttest scores provided evidence regarding the effectiveness of the intervention in improving students' mathematics learning motivation.

Research Setting

This research was conducted at SD Negeri Cileungsir during the 2025/2026 academic year. The school was selected because it had adequate technological infrastructure to support the implementation of artificial intelligence-based adaptive learning and demonstrated willingness to participate in educational innovation research. Furthermore, preliminary observations indicated that many students experienced difficulties maintaining motivation during mathematics learning activities, making the school an appropriate setting for investigating interventions aimed at enhancing learning motivation.

The research implementation was integrated into regular classroom activities to maintain ecological validity and ensure that the findings reflected authentic educational conditions. All instructional activities were conducted during official mathematics learning sessions according to the school's academic schedule. The learning materials used in both groups were aligned with the elementary mathematics curriculum and focused on topics appropriate for fourth-grade students.

Population and Sample

The population of this study consisted of all fourth-grade students enrolled at SD Negeri Cileungsir during the 2025/2026 academic year. The target population was selected because fourth-grade students have generally developed sufficient cognitive and emotional maturity to provide reliable responses regarding their learning motivation while still representing the elementary education level that constitutes the focus of this study.

The sampling process employed a purposive sampling technique. Purposive sampling was selected because the researchers needed to identify classes that met specific research requirements, including similar academic characteristics, equivalent curriculum exposure, and comparable learning environments (Etikan & Bala, 2017). Based on discussions with school administrators and classroom teachers, two classes were selected as research participants.

The final sample consisted of 60 students divided into two groups. Class 4A, consisting of 30 students, was assigned as the experimental group and received artificial intelligence-based adaptive learning. Class 4B, also consisting of 30 students, served as the control group and received conventional mathematics instruction. Prior to intervention implementation, baseline equivalence between groups was examined through pretest analysis to ensure that both groups possessed relatively similar levels of mathematics learning motivation.

The sample size was considered adequate for quasi-experimental analysis because previous educational research has demonstrated that group sizes of approximately 30 participants are sufficient to detect moderate treatment effects when appropriate statistical procedures are employed (Cohen et al., 2018). Furthermore, the sample represented the entire accessible population of fourth-grade students within the research setting, thereby enhancing the practical relevance of the findings.

Artificial Intelligence-Based Adaptive Learning Intervention

The intervention implemented in the experimental group consisted of an artificial intelligence-based adaptive learning system specifically designed to personalize mathematics learning experiences according to individual student characteristics and performance. The adaptive learning platform continuously analyzed student responses, learning progress, completion time, and mastery levels to determine appropriate learning pathways and instructional support.

The system incorporated machine learning algorithms that adjusted the difficulty level of learning materials based on students' demonstrated competence. Students who successfully completed learning activities received more challenging tasks, whereas students experiencing difficulties were provided with additional explanations, scaffolded exercises, and remedial learning opportunities. This adaptive mechanism ensured that each student encountered learning experiences aligned with their current readiness level.

The platform also provided immediate feedback following each learning activity. Correct responses were reinforced through positive feedback messages, while incorrect responses triggered explanatory guidance intended to facilitate conceptual understanding. Such immediate feedback mechanisms were expected to enhance students' perceptions of competence and support the development of positive motivational beliefs.

In addition to adaptive content delivery, the platform incorporated progress-tracking features that allowed students to monitor their learning achievements. Visual representations of learning progress were intended to strengthen students' sense of accomplishment and encourage continued engagement with mathematics learning activities. The system therefore combined personalization, feedback, and self-monitoring functions to create a learning environment conducive to motivational development.

Data Collection Procedures

Data collection was conducted systematically in several stages to ensure the accuracy and reliability of the research findings. Prior to data collection, ethical approval and institutional permission were obtained from relevant authorities, including school administrators, classroom teachers, and parents or guardians of participating students. Participants were informed regarding the purpose of the study, the voluntary nature of participation, and the confidentiality of collected information.

The initial stage involved administration of a mathematics learning motivation questionnaire as a pretest. The pretest was conducted before implementation of the instructional intervention to establish baseline motivational levels among participants. Students completed the questionnaire under researcher supervision to ensure consistency in administration procedures.

Following the pretest, the experimental group participated in mathematics learning activities utilizing the artificial intelligence-based adaptive learning platform, whereas the control group participated in conventional mathematics instruction. The intervention period lasted eight weeks, during which both groups received equivalent instructional content covering the same curriculum objectives.

At the conclusion of the intervention period, the mathematics learning motivation questionnaire was administered again as a posttest. The posttest procedures were identical to those used during the pretest phase. The resulting data provided information regarding changes in students' mathematics learning motivation attributable to the instructional treatments.

Research Instrument

The primary instrument employed in this study was a mathematics learning motivation questionnaire developed based on contemporary motivational theories and previous educational research. The instrument was designed to measure multiple dimensions of learning motivation relevant to elementary mathematics education, including learning interest, learning persistence, self-confidence, task engagement, achievement orientation, and willingness to overcome learning challenges.

The questionnaire utilized a five-point Likert scale ranging from strongly disagree to strongly agree. This scale was selected because it allows respondents to express varying degrees of agreement with motivational statements while generating quantitative data suitable for statistical analysis (Joshi et al., 2015). Positive and negative statements were included to minimize response bias and improve measurement accuracy.

Instrument development began with an extensive review of literature related to learning motivation, mathematics education, and educational psychology. The initial item pool was constructed based on established theoretical frameworks, including self-determination theory and expectancy-value theory. The draft instrument was subsequently evaluated by experts in elementary education, educational psychology, and educational measurement to establish content validity.

Content validity assessment focused on evaluating item relevance, clarity, representativeness, and alignment with the construct of mathematics learning motivation. Expert feedback was used to revise and refine questionnaire items before pilot testing. This process ensured that the instrument adequately represented the conceptual dimensions underlying mathematics learning motivation.

Instrument Validity and Reliability

Prior to its use in the main study, the questionnaire underwent validity and reliability testing through a pilot study involving students with characteristics similar to those of the research participants. Construct validity was examined using item-total correlation analysis. Items demonstrating satisfactory correlation coefficients were retained, whereas items failing to meet established criteria were revised or removed.

Reliability testing was conducted using Cronbach's Alpha coefficient to assess the internal consistency of the instrument. Internal consistency reliability is particularly important for motivational measures because it indicates the extent to which questionnaire items consistently measure the same underlying construct (Taber, 2018). The reliability analysis indicated that the instrument possessed a high level of internal consistency, thereby supporting its suitability for use in the present study.

Additional procedures were implemented to enhance measurement quality, including standardized administration protocols, clear instructions for participants, and supervision during questionnaire completion. These measures minimized potential sources of measurement error and improved data accuracy.

Data Analysis Techniques

The collected data were analyzed using both descriptive and inferential statistical techniques. Descriptive statistical analysis was employed to summarize students' mathematics learning motivation scores in terms of mean values, standard deviations, minimum scores, maximum scores, and motivational categories. Descriptive analysis provided an overview of motivational conditions before and after the intervention while facilitating comparison between experimental and control groups.

Motivational scores were interpreted using predetermined categorization criteria to facilitate meaningful understanding of students' motivational levels. Categorization enabled researchers to describe whether students' mathematics learning motivation fell within very low, low, moderate, high, or very high levels. Such interpretation supported the practical significance of the research findings and enhanced their educational relevance.

Inferential statistical analysis was conducted to test the research hypotheses regarding the effectiveness of artificial intelligence-based adaptive learning. Prior to hypothesis testing, statistical assumption tests were performed to ensure compliance with parametric analysis requirements. Normality testing was conducted to determine whether the distribution of motivational scores approximated a normal distribution. Homogeneity testing was subsequently performed to assess whether variance distributions between groups were statistically equivalent.

Following confirmation that statistical assumptions had been satisfied, hypothesis testing was conducted using paired-sample t-tests and independent-sample t-tests. The paired-sample t-test was used to examine changes in mathematics learning motivation within each group by comparing pretest and posttest scores. This analysis enabled identification of motivational improvements occurring during the intervention period.

The independent-sample t-test was used to compare posttest motivation scores between the experimental and control groups. This analysis determined whether students exposed to artificial intelligence-based adaptive learning demonstrated significantly higher levels of mathematics learning motivation than students receiving conventional instruction. The significance level for all statistical analyses was established at 0.05, consistent with accepted standards in educational research (Field, 2018).

Data analysis was performed using statistical software to ensure computational accuracy and analytical rigor. The combination of descriptive and inferential statistical procedures provided comprehensive evidence regarding the impact of artificial intelligence-based adaptive learning on elementary school students' mathematics learning motivation. This analytical framework enabled the study to address both practical educational questions and theoretical considerations concerning the role of adaptive learning technologies in supporting student motivation.

RESULTS

Table 1 presents the descriptive statistics of students' mathematics learning motivation scores in both the experimental and control groups before and after the intervention.

Table 1. Descriptive Statistics of Mathematics Learning Motivation Scores

Group	Test	N	Mean	SD	Minimum	Maximum	Category
Experimental	Pretest	30	62.34	8.12	48	78	Low
Experimental	Posttest	30	90.78	5.34	81	98	Very High
Control	Pretest	30	61.89	7.95	47	76	Low
Control	Posttest	30	67.12	7.21	54	82	Low

The descriptive statistical analysis demonstrates that the initial mathematics learning motivation scores of students in the experimental and control groups were relatively similar. The experimental group obtained a mean pretest score of 62.34, while the control group obtained a mean pretest score of 61.89. Both scores were classified within the low motivation category. This finding indicates that before the intervention, students in both groups exhibited comparable levels of mathematics learning motivation.

The similarity of pretest means suggests that the two groups began the study under relatively equivalent motivational conditions. Such equivalence is important because it strengthens the internal validity of the experimental design and supports subsequent comparisons between groups after treatment implementation.

A comparison of posttest scores reveals substantial differences between the two groups. Students in the experimental group achieved a mean score of 90.78, categorized as very high motivation, whereas students in the control group achieved a mean score of 67.12, which remained within the low motivation category. This difference indicates a considerable improvement in motivation among students who participated in AI-based adaptive learning.

The increase in the experimental group amounted to 28.44 points, representing a substantial shift from low motivation to very high motivation. In contrast, the control group experienced an increase of only 5.23 points. Although some improvement occurred in the control group, the magnitude of change was considerably smaller than that observed in the experimental group.

The standard deviation values also provide meaningful information regarding the distribution of motivation scores. The pretest standard deviation in the experimental group was 8.12, while the posttest standard deviation decreased to 5.34. This reduction indicates that students' motivation levels became more homogeneous following the intervention.

Similarly, the control group exhibited a slight reduction in standard deviation from 7.95 to 7.21. However, the decrease was not as substantial as that observed in the experimental group. This suggests that AI-based adaptive learning not only increased motivation but also reduced variability among students.

The lower posttest standard deviation in the experimental group indicates that most students benefited from the intervention regardless of their initial motivational level. Consequently, the treatment appears to have had a broadly positive effect across participants.

The minimum and maximum scores further support this interpretation. The minimum score in the experimental group increased from 48 to 81, indicating that even the least motivated students demonstrated considerable improvement. Meanwhile, the maximum score increased from 78 to 98, suggesting that highly motivated students also benefited from the intervention.

The descriptive statistics provide preliminary evidence that AI-based adaptive learning contributed to significant improvements in students' mathematics learning motivation. Before conducting hypothesis testing, prerequisite analyses were performed to evaluate the assumptions of normality and homogeneity.

Table 2. Normality Test Results

Group	Test	Sig. Value	Decision
Experimental	Pretest	0.200	Normal
Experimental	Posttest	0.186	Normal
Control	Pretest	0.173	Normal
Control	Posttest	0.164	Normal

The normality test results indicate that all significance values exceeded 0.05. Therefore, the data distributions for both groups satisfied the assumption of normality. The experimental group produced significance values of 0.200 and 0.186 for pretest and posttest scores, respectively. Both values indicate normally distributed data. Similarly, the control group generated significance values of 0.173 and 0.164 for pretest and posttest scores. These findings confirm that the data met the requirements for subsequent parametric analyses.

The fulfillment of the normality assumption indicates that the observed score distributions adequately approximated a normal distribution, thereby supporting the use of t-test procedures. Because all datasets satisfied the normality requirement, no nonparametric alternatives were necessary. The consistency of normality findings across groups also strengthens confidence in the reliability of the statistical analyses. Following the normality test, homogeneity testing was conducted.

Table 3. Homogeneity Test Results

Variable	Levene Statistic	Sig. Value	Decision
Posttest Motivation Scores	1.278	0.264	Homogeneous

The homogeneity test yielded a significance value of 0.264, which exceeded the threshold value of 0.05. This result indicates that the variance of motivation scores between the experimental and control groups was statistically homogeneous. Homogeneity of variance is an important requirement for independent-sample t-tests because it ensures that group comparisons are conducted under equivalent statistical conditions.

The fulfillment of this assumption supports the validity of subsequent hypothesis testing. The results indicate that the observed differences in motivation scores are unlikely to be attributable to unequal variance structures between groups. Consequently, the independent-sample t-test could be applied with confidence. After all assumptions were met, hypothesis testing was conducted using paired-sample and independent-sample t-tests.

Table 4. Paired-Sample t-Test Results

Group	Mean Difference	t-value	Sig. (2-tailed)	Decision
Experimental	28.44	18.763	0.000	Significant
Control	5.23	2.871	0.007	Significant

The paired-sample t-test results reveal a statistically significant increase in mathematics learning motivation within the experimental group. The significance value of 0.000 was substantially lower than the alpha level of 0.05. This finding indicates that AI-based adaptive learning produced a significant positive change in students' mathematics learning motivation. The mean difference of 28.44 points demonstrates a strong practical impact of the intervention.

Although the control group also showed a statistically significant increase, the magnitude of improvement was considerably smaller. The difference between the two groups highlights the superior effectiveness of AI-based adaptive learning. The large t-value observed in the experimental group further confirms the strength of the intervention effect.

These findings indicate that personalized learning experiences contribute substantially to motivational enhancement. To compare posttest scores between groups, an independent-sample t-test was conducted.

Table 5. Independent-Sample t-Test Results

Variable	Mean Difference	t-value	Sig. (2-tailed)	Decision
Posttest Motivation Scores	23.66	14.527	0.000	Significant

The independent-sample t-test produced a significance value of 0.000, which was lower than 0.05. This result indicates a statistically significant difference between the posttest motivation scores of the experimental and control groups.

Students who participated in AI-based adaptive learning demonstrated significantly higher motivation than students who received conventional instruction. The mean difference of 23.66 points indicates a substantial practical advantage for the experimental group. The results therefore support the research hypothesis that AI-based adaptive learning positively influences elementary school students' mathematics learning motivation.

The inferential findings reinforce the descriptive statistics by confirming that the observed differences were not attributable to random variation. Taken together, the statistical analyses provide robust evidence supporting the effectiveness of AI-based adaptive learning in improving mathematics learning motivation.

The results demonstrate both statistical significance and educational significance. Consequently, AI-based adaptive learning can be considered an effective instructional alternative for enhancing motivation in elementary mathematics education.

DISCUSSION

The findings of this study demonstrate that artificial intelligence-based adaptive learning has a significant positive effect on elementary school students' mathematics learning motivation. The substantial increase in motivation observed in the experimental group indicates that personalized instructional environments can address motivational challenges frequently encountered in mathematics education.

One of the most important findings is the transformation of students' motivation levels from the low category to the very high category after the intervention. This result suggests that adaptive learning environments can fundamentally alter students' attitudes and engagement toward mathematics learning. Such findings are consistent with the principles of self-determination theory, which emphasizes that learners become more motivated when educational experiences support their autonomy and competence (Ryan & Deci, 2020).

The considerable increase in the experimental group's mean score demonstrates that motivation is not a fixed characteristic but rather a dynamic construct that can be enhanced through appropriate instructional interventions. This finding supports previous research indicating that learning environments play a critical role in shaping students' motivational beliefs and behaviors (Eccles & Wigfield, 2020).

The adaptive nature of the learning system likely contributed significantly to the observed improvements. By continuously adjusting instructional content to match students' readiness levels, the platform provided learning experiences that were neither excessively difficult nor insufficiently challenging. Such optimal challenge conditions are known to foster engagement and intrinsic motivation (Tomlinson, 2017).

Another noteworthy finding concerns the reduction in score variability among students in the experimental group. The decrease in standard deviation suggests that the intervention benefited not only high-performing students but also learners with initially low motivation. This finding highlights the inclusive potential of adaptive learning technologies. The ability of AI systems to personalize instruction for individual learners may explain this outcome. Traditional classrooms often struggle to accommodate diverse learner needs simultaneously, whereas adaptive systems can provide individualized pathways for each student (Holmes et al., 2019).

The substantial improvement in minimum motivation scores further reinforces this interpretation. Students who initially demonstrated the lowest levels of motivation showed remarkable progress after participating in adaptive learning activities. This finding suggests that AI-based adaptive learning may be particularly effective for supporting learners who are at risk of disengagement. Immediate feedback is another factor that likely contributed to increased motivation. Research consistently indicates that timely and informative feedback strengthens learners' perceptions of competence and supports self-regulated learning behaviors (Wisniewski et al., 2020). The adaptive platform used in this study provided continuous feedback, allowing students to monitor and improve their performance effectively.

The observed motivational gains may also be explained by increased perceptions of autonomy. Students in adaptive learning environments often have greater control over learning pace, progression, and task completion. Such autonomy-supportive conditions are known to enhance intrinsic motivation and learning persistence (Ryan & Deci, 2020).

The findings are consistent with previous studies reporting positive effects of adaptive learning technologies on student engagement and motivation (Walkington & Bernacki, 2020). However, the present study extends existing literature by focusing specifically on elementary school mathematics learning motivation within an Indonesian educational context.

The results also align with the growing body of evidence regarding the educational potential of artificial intelligence. Recent reviews have highlighted the capacity of AI technologies to facilitate personalized learning and improve educational outcomes across diverse contexts (Zawacki-Richter et al., 2019; Ouyang & Jiao, 2021).

The significant difference between experimental and control groups suggests that conventional instructional approaches may be insufficient for addressing contemporary motivational challenges. While the control group demonstrated slight improvement, the magnitude of change was substantially lower than that achieved through adaptive learning.

This finding underscores the importance of personalization in modern education. Personalized learning experiences allow students to interact with content that reflects their individual needs, preferences, and competencies, thereby enhancing motivation and engagement (Holmes & Tuomi, 2022).

The present findings are also compatible with constructivist learning theory, which emphasizes active learner engagement in knowledge construction processes (Piaget, 1972; Vygotsky, 1978). Adaptive learning systems support constructivist principles by enabling students to progress through learning pathways based on their individual understanding and experiences.

Mathematics is often associated with anxiety and negative perceptions among elementary school students. The positive motivational outcomes observed in this study suggest that adaptive learning may help mitigate such challenges by creating supportive and responsive learning environments.

The intervention's effectiveness may additionally be attributed to increased opportunities for mastery experiences. According to motivational theory, successful learning experiences contribute to stronger self-efficacy beliefs and greater willingness to engage in future learning activities (Bandura, 1997). Adaptive learning environments facilitate such experiences by matching task difficulty to learner capabilities.

The findings also have important implications for educational equity. Because adaptive learning systems can provide individualized support to students with varying abilities, they may help reduce motivational disparities within classrooms. This characteristic is particularly valuable in elementary education, where learner diversity is substantial. From a practical perspective, the results suggest that teachers can utilize AI-based adaptive learning as a complementary instructional strategy rather than as a replacement for traditional teaching. The technology provides personalized support while teachers continue to facilitate broader learning experiences and social interactions.

The study contributes to the growing discourse concerning digital transformation in education. As educational institutions increasingly integrate artificial intelligence into learning environments, empirical evidence regarding its effectiveness becomes essential. The present findings provide such evidence by demonstrating measurable motivational benefits among elementary school learners.

Nevertheless, the findings should be interpreted within the context of the study's limitations. The research involved a relatively limited sample from a single elementary school, which may affect the generalizability of results. Future studies should involve larger and more diverse samples across multiple educational settings.

Future research may also investigate additional outcomes associated with AI-based adaptive learning, including mathematical achievement, self-efficacy, problem-solving skills, learning engagement, and long-term retention. Such investigations would provide a more comprehensive understanding of the educational impacts of adaptive technologies.

The findings indicate that artificial intelligence-based adaptive learning represents a promising innovation for enhancing mathematics learning motivation among elementary school students. The significant improvements observed in motivational outcomes support the integration of adaptive learning technologies into elementary mathematics instruction and contribute valuable evidence to the expanding field of artificial intelligence in education.

CONCLUSION

This study concludes that artificial intelligence-based adaptive learning has a positive and statistically significant effect on elementary school students' mathematics learning motivation. The findings indicate that students who participated in adaptive learning experienced a substantial increase in motivation, as reflected in the improvement of average motivation scores from the low category before the intervention to the very high category after the intervention. In contrast, students who received conventional instruction showed only a modest increase in motivation. The results of both descriptive and inferential analyses consistently demonstrate that the adaptive learning approach provided more favorable motivational outcomes than traditional learning methods. These findings suggest that artificial intelligence-based adaptive learning can serve as a promising instructional alternative for supporting mathematics learning motivation in elementary education, particularly by providing learning experiences that are responsive to students' individual needs and learning progress. Future studies involving larger samples, longer intervention periods, and different educational contexts are needed to further strengthen the evidence regarding the effectiveness and broader applicability of this approach.

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