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The Effect of Adaptive Learning Based E-Learning Implementation on High School Student Learning Outcomes and Motivation in The Era of Digital Transformation

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ABSTRACT

This study aims to analyze the effect of implementing an adaptive learning-based e-learning platform on the learning outcomes and motivation of senior high school (SMA) students in the context of digital transformation of education in Indonesia. The research approach used was a quasi-experimental with a pretest-posttest control group design, involving 120 eleventh-grade students from four senior high schools in Sidoarjo City selected by purposive sampling. The experimental group used the adaptive e-learning platform for 12 weeks, while the control group used conventional learning assisted by a static LMS. Data were collected through learning outcome tests, motivation questionnaires (ARCS model), and observations of student engagement. Data analysis was performed using ANCOVA, paired t-test, and multiple linear regression analysis. The results showed that students in the experimental group obtained an average posttest score of 82.4 (SD=7.6), significantly higher than the control group which obtained an average of 71.8 (SD=9.2) [$F(1,117) = 38.42$, $p<0.001$, $\eta^2=0.247$]. Student learning motivation in the experimental group also increased significantly, with an average score gain of 18.3 points ($p<0.001$). Regression analysis revealed that the frequency of interaction with adaptive features ($\beta=0.412$) and the level of content personalization ($\beta=0.358$) were the strongest predictors of learning outcomes. These findings underscore the significant potential of adaptive learning technology in improving learning quality and supporting the national digital transformation agenda in education.

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1. INTRODUCTION

The rapid development of information and communication technology has driven a fundamental transformation in global education, including in Indonesia. The concept of Educational Technology (EdTech) has evolved from a mere teaching aid to an integrated learning ecosystem capable of personalizing each individual's learning experience in real time [1]. The COVID-19 pandemic has catalyzed the accelerated adoption of e-learning across all levels of education, forcing educational institutions to rapidly adapt to digital learning modalities [2]. Indonesia, the government, through the Ministry of Education, Culture, Research, and Technology (Kemendikbudristek), has launched Merdeka Belajar (Freedom to Learn) as a framework for transforming national education centered on student-centered learning [2]. This program implicitly encourages the use of adaptive technology that can adjust material, pace, and learning style to suit individual students' needs [3] However, the gap between the availability of technological infrastructure and the quality of its

pedagogical implementation remains a major challenge that requires empirical study. Adaptive learning-based e-learning is one of the latest innovations in the EdTech ecosystem that integrates artificial intelligence (AI) and learning analytics to create dynamic, personalized learning paths [4] [5] This system works by analyzing student response patterns, comprehension speed, and error rates to automatically and continuously adjust the problem difficulty, content type, and presentation strategy.

Numerous international studies have demonstrated the effectiveness of adaptive learning in improving learning outcomes [6]. In a meta-analysis of 23 studies, found an average effect size of d=0.47 for adaptivelearning systems compared to traditional instruction. Meanwhile, [7] reported a significant increase in high school students' motivation to learn mathematics using an adaptive tutoring system. However, research in the Indonesian educational context is still very limited, particularly that simultaneously examines its impact on cognitive learning outcomes and motivational dimensions.

Based on this background, this study formulates two main questions: (1) Does the implementation of adaptive learning-based e-learning have a significant effect on high school students' learning outcomes compared to conventional learning assisted by a static LMS? and (2) Is there a significant difference in learning motivation between students who use adaptive learning and students who use conventional learning? This study is expected to provide an empirical contribution to the development of national EdTech policies and enrich the literature on educational technology in Indonesia.

2. METHOD

2.1. Research Design and Approach

This study used a quantitative approach with a quasi-experimental pretest-posttest non-equivalent control group design [8]. This design was chosen due to the limitations of full randomization in real school settings, where classes cannot be dissolved and reconstituted solely for research purposes. The experimental and control groups were matched using a matching technique based on previous semester report card grades and pretest scores to ensure initial equivalence. Figure 1 shows the research flow design.

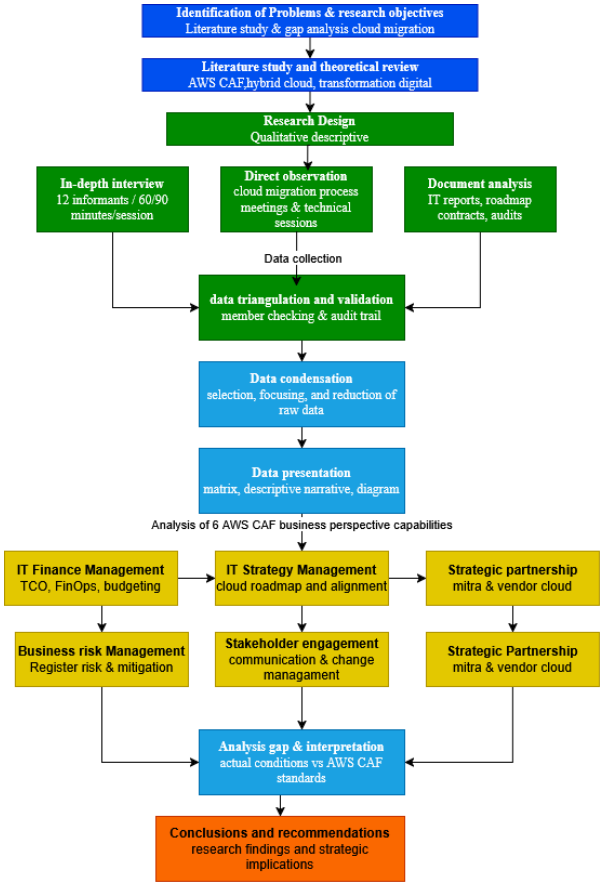


Figure 1. Research design

2.2. Population, Sample, and Sampling Techniques

The study population was all grade XI IPA students from A-accredited public and private senior high schools in Sidoarjo City for the 2024/2025 academic year, totaling approximately 2,400 students from 16 schools. The sample consisted of 120 students (60 experimental group, 60 control group) from four schools selected through purposive sampling with the following criteria: (1) having adequate internet infrastructure, (2) subject teachers willing to participate, and (3) having never implemented an adaptive learning platform before. The subject used as the intervention context was grade XI Physics, specifically the topic of Rotational Dynamics and Rigid Body Equilibrium.

2.3. Research Platforms and Instruments

The experimental group used the AdaptEd-Pro platform (version 3.2), an AI-based adaptive Learning Management System developed by a consortium of Southeast Asian universities. This platform is equipped with an Item Response Theory (IRT)-based recommendation engine and a machine learning algorithm that analyzes student response patterns every 15 minutes to dynamically adjust content. The control group used Google Classroom as a static LMS with identical materials presented uniformly without personalization. The research instruments consisted of: (1) a Physics Learning Outcome Test 30 multiple-choice questions and 5 essay questions, validated by three subject matter experts and with a Cronbach's reliability of $\alpha = 0.87$; (2) a Learning Motivation Questionnaire an adaptation of the Instructional Materials Motivation Survey (IMMS) based on the ARCS [8] model with 36 statement items ($\alpha = 0.91$); and (3) a Student Engagement Observation Sheet completed by a certified independent observer for each learning session.

2.4. Implementation Procedures

The intervention was implemented for 12 weeks (August–October 2025) with a frequency of four learning sessions per week (each 90 minutes). The research procedure included three main phases:

- Preparation Phase (2 weeks): Training teachers and platform administrators, instrument calibration, pretest administration, and outreach to students and parents.
- Intervention Phase (8 weeks): Implementation of adaptive learning in the experimental group in parallel with conventional learning in the control group, accompanied by regular observations and collection of platform log data.
- Closing Phase (2 weeks): Posttest administration, completion of motivation questionnaires, reflective interviews with a selected sample of students (n=12), and data processing.

2.5. Data Analysis Techniques

Data were analyzed using IBM SPSS Statistics version 28 and R version 4.3.1. After testing the assumptions of normality (Shapiro-Wilk) and homogeneity of variance (Levene's test), inferential analysis was conducted through: (1) Analysis of Covariance (ANCOVA) to test differences in posttest learning outcomes with pretest scores as covariates; (2) paired t-test to compare motivation gain scores within groups; and (3) Multiple Linear Regression to identify predictors of learning outcomes from platform feature usage variables. The significance level was set at $\alpha = 0.05$ with two-tailed testing.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

Table 1 presents a summary of descriptive statistics of the learning test results and motivation scores of both groups before and after the intervention.

Table 1. Descriptive Statistics of Learning Outcomes and Motivation of the Two Groups

Variable	Group	Pretest M (SD)	Postest M (SD)	Gain Score
Study result	Experiment(n=60)	56,7 (8,4)	82,4 (7,6)	+25,7
Study result	Control (n=60)	55,9 (9,1)	71,8 (9,2)	+15,9
Motivation (ARCS)	Experiment (n=60)	102,3 (12,1)	120,6 (10,8)	+18,3
Motivation (ARCS)	Control (n=60)	103,8 (11,7)	110,5 (12,3)	+6,7

3.2. Hypothesis Testing Effect on Learning Outcomes

Prior to the ANCOVA test, the Shapiro-Wilk normality test showed that the distribution of posttest scores in both the experimental (W=0.976, p=0.297) and control (W=0.971, p=0.218) groups did not deviate significantly from a normal distribution. Levene's test indicated homogeneity of variance (F=1.842, p=0.178). The linearity test for the covariate (pretest) and the dependent variable (posttest) was also met (F=2.14,

p=0.147). The ANCOVA results showed a statistically significant difference between the posttest scores of the experimental and control groups after controlling for pretest scores [F (1,117) =38.42, $p<0.001$, $\eta^2=0.247$]. The partial eta-squared value ($\eta^2=0.247$) indicates that the adaptive learning intervention explained approximately 24.7% of the variance in posttest scores, which, according to Cohen's criteria [7], falls within the large effect size category. The adjusted mean difference between the two groups was 9.8 points (95% CI [7.2; 12.4]). This finding aligns with Pane & Steiner's meta-analysis [9], which found a positive effect size for adaptive learning systems, and Abdi et al.'s study [10], which reported significant improvements in physics learning outcomes for high school students in Malaysia using an AI-based adaptive platform. The suspected mechanism is just-in-time scaffolding the system automatically provides additional instructions or examples when students demonstrate consistent error patterns, thus preventing the accumulation of misconceptions that often occur in physics learning [11].

3.3. Hypothesis Testing Influence on Learning Motivation

A paired t-test comparing ARCS motivation score gains revealed that the increase in motivation in the experimental group (M=+18.3, SD=8.2) was significantly greater than in the control group (M=+6.7, SD=7.9) [t (118) =8.63, $p<0.001$, d=1.43]. Cohen's d effect size of 1.43 indicates a significant difference in practical terms. Analysis by ARCS dimension revealed that the Confidence dimension experienced the greatest increase in the experimental group (Δ=6.8 points), followed by Relevance (Δ=4.9 points), Satisfaction (Δ=3.8 points), and Attention (Δ=2.8 points). This pattern indicates that the instant feedback and visualization features of learning progress on adaptive platforms are particularly effective in building students' self-efficacy in line with Bandura's [12] theory on the role of mastery experience in the formation of academic self-efficacy [13].

3.4. Factors Predicting Learning Outcomes

A multiple linear regression analysis using four primary predictors from the platform log data (frequency of adaptive feature interaction, level of content personalization, duration of learning sessions per week, and number of remedial courses completed) yielded a significant model [F (4,55) =22.7, $p<0.001$, $R^2=0.623$]. This model explained 62.3% of the variance in the experimental group's posttest scores. Frequency of interaction with adaptive features ($\beta=0.412$, t=4.87, $p<0.001$) and the level of content personalization achieved by students ($\beta=0.358$, t=3.94, $p<0.001$) were the two strongest predictors. These findings imply that the effectiveness of adaptive learning is not automatic but rather depends heavily on students' level of active engagement with the available adaptive features. Students who proactively utilize diagnostic quiz features, recommended remedial videos, and enrichment modules tend to achieve higher content personalization and, consequently, better learning outcomes.

3.5. Implications and Limitations of the Research

The findings of this study have several important implications. First, for EdTech platform developers, interface design that encourages exploration of adaptive features (such as smart notifications and progress gamification) needs to be prioritized to maximize student engagement. Second, for teachers and schools, effective implementation of adaptive learning requires a shift in the teacher's role from information provider to digital learning facilitator and manager competent in interpreting platform analytics data. Third, for policymakers, these findings support the importance of sustained investment in school digital infrastructure as a prerequisite for the equitable use of adaptive technology. This study has several limitations that should be noted. The limited sample size to one city and one subject limit the generalizability of the findings. The 12-week intervention duration does not allow for measuring the long-term impact of adaptive learning on knowledge retention and learning transfer. Furthermore, the Hawthorne effect in the experimental group cannot be completely ruled out. Further research with larger, multidisciplinary, and multi-city samples is highly recommended.

4. CONCLUSION

This study empirically demonstrates that the implementation of adaptive learning based e-learning has a significant and substantial impact on high school students' physics learning outcomes ($\eta^2=0.247$, large effect size) compared to conventional learning supported by a static LMS. With an adjusted mean difference of 9.8 points, the adaptive platform proved to be more effective in improving students' cognitive achievement. The motivational dimension also showed a very positive response to the adaptive learning intervention, with a significantly greater increase in learning motivation in the experimental group (Cohen's d=1.43). The Confidence and Relevance dimensions of the ARCS model experienced the greatest improvement, indicating that content personalization and instant feedback were effective in building students' confidence and perceived learning relevance.

Key factors determining the effectiveness of adaptive learning were students' active engagement with the platform's adaptive features (β=0.412) and the level of content personalization achieved (β=0.358). This confirms that adaptive technology is not a silver bullet; it requires appropriate pedagogical design, comprehensive teacher training, and adequate student digital literacy to optimize its impact.

Overall, this research supports the argument that integrating adaptive learning technology into the Indonesian education system has significant potential to improve the quality and equity of learning outcomes, in line with the vision of digital transformation of national education within the Merdeka Belajar framework. Multi-stakeholder commitment the government, the EdTech industry, educational institutions, and the teacher communit is needed to realize an inclusive and sustainable adaptive learning ecosystem in Indonesia.

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