TARBIYA: Journal of Education in Muslim Society, 12(2), 2025, 163-178
DOI: http://doi.org/10.15408/tjems.v12i2.46582
Website: http://journal.uinjkt.ac.id/index.php/tarbiya
p-ISSN: 2356-1416, e-ISSN: 2442-9848

DEVELOPMENT OF EDUSMART AS AN AI-BASED ADAPTIVE LEARNING APPLICATION FOR NEEDS ANALYSIS AMONG INDONESIAN PRIMARY SCHOOL STUDENTS

Titin Sunaryati*, Edi Widodo, Ahmad Firdaus, Muhamad Sudharsono, Muhammad Faiz Rayyan
Universitas Pelita Bangsa, Indonesia
E-mail: titin.sunaryati@pelitabangsa.ac.id

Received: 29th June 2025; Revised: 15th August 2025; Accepted: 28th December 2025

Abstract

Digital transformation in primary education requires learning tools that can support competency-based assessment and respond to students' diverse learning needs. However, conventional evaluation practices often provide limited diagnostic information for teachers when planning differentiated instruction. This study aimed to develop and conduct an initial classroom trial of EduSmart, an AI-supported adaptive learning application designed to classify students' competency levels and provide learning recommendations based on quiz performance. The study employed a Research and Development (R&D) approach using the ADDIE model. Participants consisted of 66 fifth-grade students from three public elementary schools in Bekasi Regency. Data were collected through observations, interviews, expert validation, user response questionnaires, and learning outcome tests using a one-group pretest–posttest design. Quantitative data were analyzed using descriptive statistics, paired-sample t-test, and N-Gain analysis, while qualitative data were analyzed thematically with NVivo support. The results showed that EduSmart was rated very feasible by experts, with an average score of 4.5 out of 5. The paired-sample t-test indicated a significant difference between pretest and posttest scores ($p < .001$), with a mean improvement of 15.68 points. The average N-Gain score was 0.42, indicating moderate improvement. Qualitative findings showed that students responded positively to EduSmart, particularly in terms of ease of use, learning relevance, and motivation. Since the study did not involve a control group, these findings should be interpreted as preliminary evidence of EduSmart's potential to support adaptive and data-informed learning in primary education.

Keywords: EduSmart, artificial intelligence, adaptive learning, AI-based formative assessment, primary education

Abstrak

Transformasi digital dalam pendidikan dasar membutuhkan perangkat pembelajaran yang mampu mendukung asesmen berbasis kompetensi dan merespons kebutuhan belajar siswa yang beragam. Namun, praktik evaluasi konvensional sering kali belum memberikan informasi diagnostik yang cukup bagi guru dalam merancang pembelajaran terdiferensiasi. Penelitian ini bertujuan mengembangkan dan melakukan uji coba awal aplikasi EduSmart, yaitu aplikasi pembelajaran adaptif berbasis AI yang dirancang untuk mengklasifikasikan tingkat kompetensi siswa dan memberikan rekomendasi belajar berdasarkan hasil kuis. Penelitian ini menggunakan pendekatan Research and Development (R&D) dengan model ADDIE. Partisipan penelitian terdiri atas 66 siswa kelas V dari tiga sekolah dasar negeri di Kabupaten Bekasi. Data dikumpulkan melalui observasi, wawancara, validasi ahli, angket respons pengguna, serta tes hasil belajar dengan desain one-group pretest–posttest. Data kuantitatif dianalisis menggunakan statistik deskriptif, paired-sample t-test, dan N-Gain, sedangkan data kualitatif dianalisis secara tematik dengan bantuan NVivo. Hasil penelitian menunjukkan bahwa EduSmart dinilai sangat layak oleh ahli dengan skor rata-rata 4,5 dari 5. Hasil paired-sample t-test menunjukkan perbedaan yang signifikan antara skor pretest dan posttest ($p < .001$), dengan peningkatan rata-rata sebesar 15,68 poin. Nilai rata-rata N-Gain sebesar 0,42 menunjukkan peningkatan pada kategori sedang. Temuan kualitatif menunjukkan bahwa siswa merespons EduSmart secara positif, terutama pada aspek kemudahan penggunaan, relevansi pembelajaran, dan motivasi belajar. Karena penelitian ini tidak menggunakan kelompok kontrol, temuan tersebut perlu dipahami sebagai bukti awal mengenai potensi EduSmart dalam mendukung pembelajaran adaptif dan berbasis data di pendidikan dasar.

***Kata kunci**: EduSmart, artificial intelligence, pembelajaran adaptif, asesmen formatif berbasis AI, pendidikan dasar*

How to Cite: Sunaryati, T., Widodo, E., Firdaus, A., Sudharsono, M., & Rayyan, M. F. (2025). Development of Edusmart as an AI-Based Adaptive Learning Application for Needs Analysis Among Indonesian Primary School Students. *TARBIYA: Journal of Education in Muslim Society, 12*(2), 163-178. doi:10.15408/tjems.v12i2.46582.

*Corresponding author

Introduction

Modern education increasingly emphasizes competency-based learning, which focuses on mastery of essential knowledge and skills while enabling students to progress according to clearly defined standards (Açıkgöz & Babadoğan, 2021; Rich et al., 2020). In this paradigm, education systems are expected to identify students' learning profiles, provide personalized learning experiences, and support inclusive and sustainable learning processes (Alamri, 2021; Bhutoria, 2022; Kabudi et al., 2021). However, the implementation of competency-based learning in primary schools still faces significant challenges, particularly in identifying individual students' needs and formulating appropriate learning recommendations (Tandika & Ndijuye, 2020). These challenges often make it difficult for teachers to design learning strategies that match students' abilities and levels of understanding. In primary education, this problem deserves particular attention because students are still building basic literacy, numeracy, and independent learning habits, all of which require continuous teacher guidance.

Conventional evaluations, such as standardized and summative tests, often provide limited information about students' actual learning difficulties. They may show whether a student has answered correctly or incorrectly, but they do not always explain why the student experienced difficulty or what kind of support is needed afterward. Observations and interviews with primary school teachers in Bekasi Regency showed that teachers still face challenges in designing appropriate learning strategies because current assessment practices provide limited diagnostic feedback. Large-scale or standardized tests may also be influenced by contextual factors and may not fully capture students' competencies (de Hoyos et al., 2021). For this reason, assessment in primary education needs to move beyond measuring final scores and should provide clearer information about students' learning progress, areas of weakness, and possible follow-up activities (Choi & McClenen, 2020; Minn, 2022).

Artificial Intelligence (AI) can support this need when it is used to analyze learning data and provide feedback for teachers and students. AI technologies, including machine learning and knowledge-assessment models, can help identify learning patterns, recognize students' strengths and weaknesses, and generate recommendations based on formative assessment data (Bimpeh, 2024; Kabudi et al., 2021; Minn, 2022). In education, AI has been used to improve learning quality, particularly through adaptive systems and recommender systems that adjust materials or activities according to students' competency profiles (Huang et al., 2023; Parkavi et al., 2024; Yanes et al., 2020). Learning analytics can also support teachers in interpreting student performance data and planning timely interventions (Seo et al., 2021; Waheed et al., 2020). For teachers, this kind of system can serve as a practical source of information for deciding which students need remedial support, enrichment activities, or differentiated instruction.

In Indonesia, the use of technology to support adaptive and competency-based learning is in line with the Merdeka Curriculum policy, as stated in Regulation of the Minister of Education, Culture, Research, and Technology Number 12 of 2024, and with the Strategic Plan of the Ministry of Education and Culture 2020–2024, which emphasizes digital transformation in education (Ministry of Education and Culture, 2020; Ministry of Education, Culture, Research,

DOI: 10.15408/ tjems.v12i2.46582

and Technology, 2024). This orientation is also consistent with broader discussions on AI-supported educational transformation (Cantú-Ortiz et al., 2020; UNESCO, 2023). Based on this context, the present study develops EduSmart, an AI-supported adaptive learning application designed to analyze students' learning needs, provide learning recommendations, and help teachers plan more suitable instructional strategies. EduSmart is not intended to replace the role of teachers, but to assist them in reading students' learning data more systematically and using that information for classroom decision-making.

The main issue addressed in this study is the limited availability of AI-supported adaptive learning applications designed for primary school students and suited to Indonesian classroom conditions. Previous studies have shown that competency-based learning can contribute to educational quality, yet many of these studies have not integrated AI for real-time or near-real-time learning needs analysis (Açıkgöz & Babadoğan, 2021; Rich et al., 2020; Stefanov, 2022). Other studies have examined adaptive learning systems, formative assessment systems, or recommender systems separately (Choi & McClenen, 2020; Kabudi et al., 2021; Yanes et al., 2020). However, there remains a need for a platform that combines learning analytics, formative assessment, and adaptive instructional recommendations in one system. This gap is particularly relevant in primary education because much of the discussion on AI-supported personalized learning still focuses on higher education or adult learning contexts (Alamri, 2021; Bhutoria, 2022).

Therefore, this study introduces EduSmart as an AI-supported adaptive learning application that combines competency analysis, personalized recommendations, and formative assessment. Unlike systems that focus mainly on adaptive testing (Choi & McClenen, 2020; Minn, 2022) or competency-based evaluation without AI-supported recommendation features (Rich et al., 2020; Stefanov, 2022), EduSmart is designed to connect assessment results with learning recommendations. The application classifies students' competency levels, identifies learning difficulties, and recommends learning activities that are more closely related to students' needs. In this sense, EduSmart functions not only as a learning application, but also as a tool for students' needs analysis in classroom learning.

The novelty of this research lies in the development and classroom implementation of an adaptive AI application for primary education in Indonesia, particularly in Bekasi Regency. While many previous studies on personalized learning focus on higher education (Alamri, 2021; Bhutoria, 2022), empirical studies involving elementary school students remain limited. This study therefore contributes to the discussion of AI-supported adaptive learning by offering a local model that can be tested in real classroom settings. Specifically, this study aims to: 1) develop the EduSmart application using the ADDIE model; 2) examine its feasibility through expert validation; 3) evaluate its effect on students' learning outcomes; and 4) describe students' and teachers' responses to the use of EduSmart in primary school learning.

Method

This study employed a Research and Development (R&D) approach using the ADDIE model, which consists of Analysis, Design, Development, Implementation, and Evaluation. The ADDIE

DOI: 10.15408/ tjems.v12i2.46582

model was used because it provides a systematic framework for developing and evaluating instructional products through iterative stages of needs analysis, design, development, implementation, and evaluation (Branch, 2009). In this study, the model was applied to develop the EduSmart application and examine its feasibility, practicality, and initial effectiveness in supporting AI-based adaptive learning in primary schools.

The study also used a mixed-method approach. Quantitative data were obtained from expert validation, user response questionnaires, and pretest–posttest results, while qualitative data were collected through observations, interviews, and user feedback (Creswell, 2014). The classroom trial used a one-group pretest–posttest design to compare students' learning outcomes before and after using EduSmart. Since this design did not involve a control group, the findings were interpreted as initial evidence of effectiveness rather than definitive causal evidence (Shadish et al., 2002).

Research Participants

The study was conducted in three public elementary schools in Bekasi Regency, West Java. The participants consisted of 66 fifth-grade students. The schools were selected purposively based on their technology readiness and willingness to implement competency-based learning, which is consistent with purposive sampling procedures in mixed-method implementation research (Palinkas et al., 2015). In addition to students, four teachers and three school principals were involved as supporting informants to provide qualitative insights regarding the practicality and classroom relevance of EduSmart, see table 1.

Table 1. Distribution of Research Subjects

No.	School Name	Number of Class V Students
1	SDN Pasirsari 03	23
2	SDN Sukaresmi 06	22
3	SDN Cijengkol 03	21
	Total	**66**

Development Procedure

The development of EduSmart followed the five stages of the ADDIE model. First, the analysis stage was conducted to identify students' learning difficulties, limitations of existing assessment practices, and teachers' needs for adaptive learning support. Data were collected through classroom observations, teacher interviews, and student questionnaires.

Second, the design stage focused on developing the application workflow, user interface, learning materials, assessment instruments, and AI-based recommendation framework. EduSmart was designed to collect student quiz data, classify students' competency levels, and provide learning recommendations based on their needs.

Third, the development stage involved producing the EduSmart prototype as a web-based adaptive learning application. The application was designed with three main functions: collecting student performance data, analyzing competency levels, and generating learning recommendations.

DOI: 10.15408/ tjems.v12i2.46582

Expert validation was then conducted by three experts in educational technology, artificial intelligence, and competency-based learning. The validation assessed interface design, interactivity, AI functionality, relevance of recommendations, and pedagogical alignment using a 1–5 Likert scale.

Fourth, the implementation stage was carried out in classroom learning activities. Students completed a pretest before using EduSmart and a posttest after the learning activities. During implementation, teachers observed students' learning processes and used EduSmart feedback to identify students who needed further support.

Fifth, the evaluation stage consisted of formative and summative evaluation. Formative evaluation was conducted during the development process based on expert comments and classroom observations. Summative evaluation was conducted after implementation to assess the feasibility, practicality, and initial effectiveness of EduSmart.

Data Collection

Data were collected using five techniques: observation, interviews, expert validation, user response questionnaires, and learning outcome tests. Observation and interviews were used to identify classroom needs and user responses. Expert validation was used to evaluate the feasibility of the prototype. User response questionnaires were used to assess the practicality of the application, while pretest and posttest were used to measure changes in students' learning outcomes.

Data Analysis

Quantitative data were analyzed using descriptive statistics, paired-sample t-test, and N-Gain analysis. Expert validation and user response data were analyzed by calculating average scores and percentages. Before conducting the paired-sample t-test, the normality of pretest and posttest data was examined using the Kolmogorov–Smirnov and Shapiro–Wilk tests. The paired-sample t-test was then used to determine whether there was a significant difference between students' pretest and posttest scores.The N-Gain test was used to measure the level of improvement in students' learning outcomes. The N-Gain categories were classified as high (> 0.7), medium ($0.3 \leq g \leq 0.7$), and low (< 0.3) (Hake, 1998).

Qualitative data from observations, interviews, and user feedback were analyzed thematically using NVivo. The analysis followed the logic of thematic analysis by identifying patterns related to ease of use, relevance to learning needs, motivation, engagement, and teacher support in instructional decision-making (Braun & Clarke, 2006). The word cloud was used only as a supporting visualization, while the main interpretation was based on thematic patterns.

The expert validation scores were interpreted using a five-point rating scale, as presented in Table 2. This scale was used to classify each validation item from very unsuitable to very suitable. The use of a Likert-type scale is appropriate for measuring expert and user perceptions when the scale items are clearly defined (Jebb et al., 2021). After the expert scores were converted into percentages, the feasibility level of the EduSmart application was determined based on the criteria

DOI: 10.15408/ tjems.v12i2.46582

shown in Table 3. These criteria were used to decide whether the application was categorized as very feasible, feasible, moderately feasible, or not feasible.

Table 2. Validation Rating Scale

Score	Assessment Description
1	Very unsuitable
2	Not suitable
3	Fair
4	Suitable
5	Very suitable

Table 3. Feasibility Criteria

Percentage Score	Criteria
81–100%	Very feasible
61–80%	Feasible
41–60%	Moderately feasible
< 40%	Not feasible

Results and Discussion

Results

Development of the EduSmart Application

The development process resulted in a working prototype of EduSmart, an AI-supported adaptive learning platform designed to assist teachers in identifying students' learning needs and providing learning recommendations. The application was developed as a web-based platform that can be accessed through digital devices commonly used by teachers and students. It was connected to a database system and an AI analysis module that processes students' quiz data, including scores, answer accuracy, completion time, and topic difficulty level.

The system classifies students into three competency profiles: beginner, developing, and proficient. Based on this classification, EduSmart provides learning recommendations that are adjusted to students' current level of understanding. This feature is intended to support adaptive learning, in which student data are used to guide learning pathways and instructional decisions (Huang et al., 2023; Kabudi et al., 2021; Yanes et al., 2020).

Figure 1 presents the workflow of the EduSmart adaptive system. The process begins with user login, followed by quiz participation, data analysis by the AI module, competency classification, and generation of learning recommendations.

DOI: 10.15408/ tjems.v12i2.46582

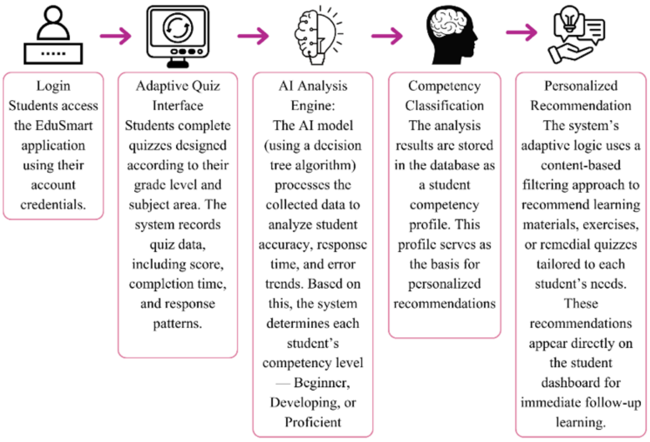
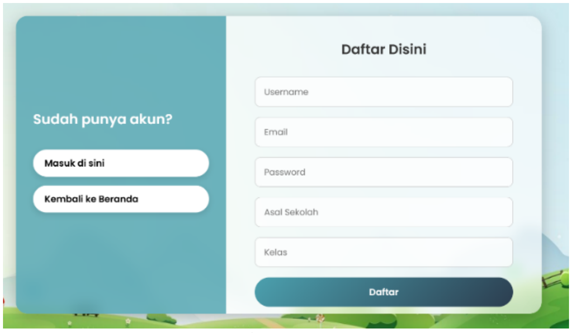
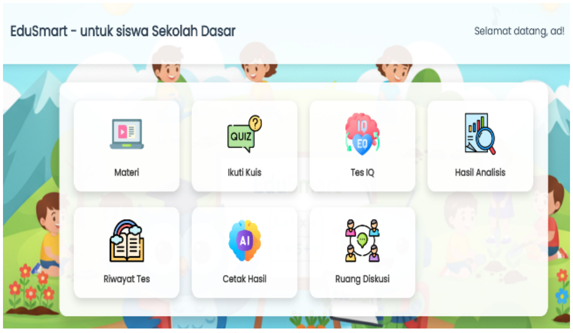


Figure 1. Workflow of the EduSmart AI Adaptive System.

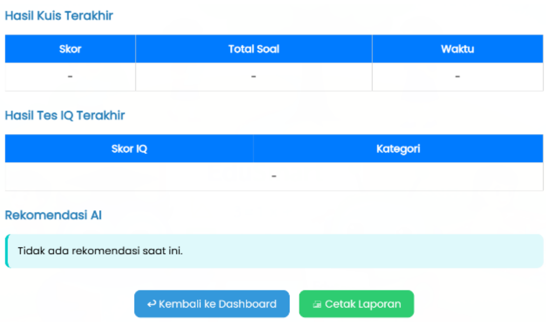
Several main interfaces were developed in the application, as shown in Figure 2. These include the home and login page, student dashboard, AI-generated recommendation page, and teacher dashboard.



Home page and registration



Student dashboard with adaptive quiz and IQ test options



AI-generated learning recommendations

Teacher dashboard showing student analytics

Figure 2. Interface Display of the EduSmart Application

Figure 2 presents the visual interface of the EduSmart adaptive learning application, which can be accessed through the web platform at https://www.educsmart.net/. The interface was designed

DOI: 10.15408/ tjems.v12i2.46582

to be simple, interactive, and child-friendly, using soft colors, rounded elements, and intuitive icons suitable for elementary school students.https://www.educsmart.net/

The application consists of four main display components:

1) Home and Login Page: This page allows students and teachers to log in to the system securely. It includes a welcoming interface with the EduSmart mascot and easy-to-read typography to build initial engagement.
2) Student Dashboard: After logging in, students are directed to a personalized dashboard containing the Take Quiz and IQ Test buttons. The dashboard provides direct access to learning activities and displays individual progress summaries based on previous sessions.
3) AI Recommendation Page: Once a student completes a quiz, the AI module analyzes the data and displays adaptive feedback. Recommendations are presented in clear, colorful cards labeled “Recommended Practice,” “Review Material,” or “Next Challenge,” guiding students toward areas that need improvement.
4) Teacher Dashboard: Teachers can view aggregated analytics showing each student’s learning progress, competency classification, and activity timeline. These analytics support teachers in planning remedial or enrichment lessons based on AI-generated insights.

This interface design reflects EduSmart’s goal of integrating artificial intelligence, formative assessment, and adaptive learning into a single platform accessible to all users without installation. Its web-based nature ensures that students can access learning materials anytime and anywhere, supporting the government’s policy of digital transformation in education and competency-based learning implementation. However, at this stage, the application should be understood as an initial prototype whose AI functionality still requires further refinement and broader testing.

Expert Validation Results

Expert validation was conducted by three specialists representing educational technology, artificial intelligence, and competency-based learning. The validation assessed five aspects: interface design, interactivity, AI functionality, relevance of learning recommendations, and pedagogical alignment.

Table 4. Expert Validation Results for the EduSmart AI-Based Adaptive Learning Application

Aspect	Average Score	Category
Interface Design	4.6	Very Feasible
Interactivity	4.5	Very Feasible
AI Functionality	4.4	Feasible
Learning Recommendation Relevance	4.6	Very Feasible
Pedagogical Alignment	4.5	Very Feasible

As shown in Table 4, the overall average validation score was 4.5 on a 5-point scale, indicating that EduSmart was considered very feasible for classroom trial. The highest scores were found in interface design and learning recommendation relevance, both scoring 4.6. This suggests that the

DOI: 10.15408/ tjems.v12i2.46582

experts viewed the application as visually appropriate and pedagogically relevant for primary school students.

The AI functionality aspect received a score of 4.4, which remained in the feasible category but was slightly lower than the other aspects. This indicates that although the AI-supported features were considered usable, further refinement is still needed, particularly in improving the accuracy, transparency, and consistency of the recommendation mechanism.

Quantitative Results

The classroom trial involved 66 fifth-grade students from three public elementary schools in Bekasi Regency. The quantitative analysis examined students' learning outcomes before and after using EduSmart. Before conducting the paired-sample t-test, the normality of the pretest and posttest data was examined using the Kolmogorov–Smirnov and Shapiro–Wilk tests. The results showed that the data met the normality assumption, with p-values greater than 0.05.

The paired-sample t-test showed a statistically significant difference between students' pretest and posttest scores after using EduSmart. The mean difference between the two tests was 15.68 points, with a significance value of $p < .001$.

Table 5. Paired Sample Test

Pair	Mean Difference	Std. Deviation	Std. Error Mean	95% CI Lower	95% CI Upper	t	df	Sig. (2-tailed)
Pretest–Posttest	-15.682	.469	.058	-15.797	-15.566	-271.445	65	.000

The paired-sample t-test showed a statistically significant difference between students' pretest and posttest scores, with a mean difference of 15.68 points and a significance value of $p < .001$. This result indicates that students' scores increased after using EduSmart. However, because this study used a one-group pretest–posttest design without a control group, the improvement should be interpreted carefully as preliminary evidence of learning improvement rather than definitive causal evidence of the application's effectiveness.

The improvement in students' learning outcomes was further examined using N-Gain analysis. The result is presented in Table 6.

Table 6. N-Gain Analysis Results

Variable	N	Minimum	Maximum	Mean	Std. Deviation
N-Gain	66	.33	.60	.4271	.06079

The average N-Gain score was 0.4271, which falls into the medium category based on Hake's classification (Hake, 1998). This result suggests that students experienced a moderate improvement in learning outcomes after using EduSmart. The finding supports the potential of EduSmart as a learning support tool, although further testing with a stronger research design is needed to confirm its effectiveness.

DOI: 10.15408/ tjems.v12i2.46582

Qualitative Results

Qualitative data were obtained from interviews, classroom observations, and user feedback. The data were analyzed thematically using NVivo to identify patterns in students' and teachers' responses to the EduSmart application. The analysis produced four main themes: ease of use, relevance to learning needs, motivation and engagement, and teacher support, see table 7.

Table 7. Themes Emerging from User Responses

Theme	Main Indication	Interpretation
Ease of use	Students found the application simple and accessible.	EduSmart was generally suitable for elementary students in terms of interface and navigation.
Relevance to learning needs	Students noticed that recommendations were related to quiz results and areas of difficulty.	The recommendation feature helped connect assessment results with follow-up learning activities.
Motivation and engagement	Students described the application as enjoyable and helpful.	The visual design and direct feedback encouraged students to participate in learning activities.
Teacher support	Teachers used the feedback to identify students needing additional guidance.	EduSmart supported teachers in planning remedial and enrichment activities.

The word cloud visualization in Figure 3 supports these thematic findings. Frequently appearing words such as belajar (learning), EduSmart, rekomendasi (recommendation), aplikasi (application), membantu (helpful), and menyenangkan (fun) show that students associated the application with learning support and positive engagement.

Figure 3. NVivo Word Cloud of Student Perceptions on the EduSmart Application

The word cloud was used as a supporting visualization rather than the main basis of qualitative interpretation. Larger words represent higher frequency in students' responses, indicating that students frequently referred to EduSmart as a helpful and enjoyable learning application. The frequent appearance of words related to recommendation and assistance also suggests that students recognized the role of the application in guiding their learning.

Overall, the qualitative findings indicate that students responded positively to EduSmart, particularly in terms of ease of use, learning relevance, and motivation. Teachers also reported that AI-generated feedback helped them identify students who required additional support. These

DOI: 10.15408/ tjems.v12i2.46582

findings suggest that EduSmart has practical value as a classroom support tool, especially for helping teachers connect assessment results with differentiated instruction.

Discussion

The findings of this study indicate that the EduSmart application has the potential to support adaptive and competency-based learning in primary education. The application integrated quiz-based assessment, competency classification, and learning recommendations into a single learning platform. Rather than claiming that EduSmart definitively improves learning outcomes, the findings should be understood as preliminary evidence that the application may contribute to students' learning improvement and provide useful diagnostic information for teachers. This interpretation is important because the classroom trial used a one-group pretest–posttest design without a control group.

The increase in posttest scores and the medium N-Gain score suggest that students experienced improvement after using EduSmart. However, this improvement cannot be attributed solely to the application because other classroom factors may also have influenced students' learning outcomes. Therefore, the quantitative findings should be interpreted as an indication of EduSmart's potential effectiveness, not as conclusive causal evidence. At the same time, the positive responses identified through NVivo analysis show that students generally perceived EduSmart as easy to use, helpful, and engaging. These findings suggest that the application may serve as a practical tool to connect assessment results with follow-up learning activities.

From a theoretical perspective, the results are consistent with the principles of adaptive learning, which emphasize that instruction should respond to learners' performance, progress, and learning needs (Kabudi et al., 2021; Minn, 2022). The recommendation system in EduSmart reflects this principle by using students' quiz data to classify competency levels and provide learning suggestions. In this sense, EduSmart does not merely function as a digital quiz platform, but as a formative learning support system that helps identify students' areas of difficulty and recommends relevant follow-up activities. This is in line with the broader idea that adaptive learning systems can use student data to support differentiated learning pathways (Choi & McClenen, 2020; Yanes et al., 2020).

Furthermore, the EduSmart design aligns with the concept of personalized education, which focuses on tailoring learning experiences to each learner's abilities, pace, and interests (Bhutoria, 2022; Huang et al., 2023). Personalized learning emphasizes the learner as an active participant in the educational process. In this study, students' interaction with the recommendation features shows a movement toward more learner-responsive instruction. However, this shift should not be interpreted as a complete replacement of teacher-centered instruction. Instead, EduSmart appears to support a more balanced learning process in which teachers remain central while student data are used to guide instructional decisions. This finding supports the framework of AI-supported learning analytics, in which AI technologies can assist teachers in providing targeted interventions based on student performance data (Bimpeh, 2024; Parkavi et al., 2024; Waheed et al., 2020).

DOI: 10.15408/ tjems.v12i2.46582

The qualitative findings strengthen this interpretation. Students' responses, especially the frequent appearance of words such as "menyenangkan" (fun), "membantu" (helpful), and "rekomendasi" (recommendation), indicate that they experienced the application as a supportive learning tool. These responses suggest that adaptive feedback may contribute to students' sense of competence and engagement, particularly when recommendations are understandable and directly related to their learning difficulties. This finding is relevant to Self-Determination Theory, which explains that motivation can be strengthened when learners experience autonomy, competence, and meaningful support in the learning process (Ryan & Deci, 2000). When students receive feedback that helps them understand what to improve, they are more likely to remain engaged in learning activities (Bosch et al., 2021). Nevertheless, the motivational effect of EduSmart should be interpreted carefully. The word cloud provides useful visual support, but it is not sufficient on its own to explain students' learning experiences. The thematic findings need to be supported by interview excerpts or observation notes in order to provide stronger qualitative evidence. Therefore, future reporting should include direct quotations from students and teachers to show how users experienced the application in real classroom situations. The teachers' responses also indicate that EduSmart may support data-informed teaching practices. The feedback generated by the application helped teachers identify students who needed remedial assistance or enrichment activities. This reflects a teacher-AI partnership model in which human expertise is complemented, not replaced, by AI's analytical capacity (Seo et al., 2021; UNESCO, 2023). This point is important because AI in education should be positioned as a decision-support tool rather than an autonomous decision-maker. Teachers still need to interpret the recommendations, consider students' classroom behavior, and decide the most appropriate instructional response. In this regard, EduSmart can be understood as a teacher-facing learning analytics tool that assists instructional planning and differentiation.

The findings also show that the AI functionality of EduSmart still requires further refinement. Although expert validation rated the AI functionality as feasible, its score was slightly lower than the interface design and recommendation relevance. This suggests that the technical and pedagogical quality of the recommendation system needs continued improvement, particularly in terms of accuracy, transparency, and consistency. If EduSmart is to be used more widely, the recommendation logic should be tested with larger datasets, broader subject areas, and more diverse student profiles.

Overall, this study contributes to the discussion of AI-supported adaptive learning in primary education by offering a locally developed application tested in Indonesian elementary school settings. Its contribution lies not in proving the full effectiveness of AI-based learning, but in showing how an adaptive learning prototype can be developed, validated, and initially tested in classroom practice. This contribution is relevant because empirical studies on AI-supported adaptive learning at the elementary school level, especially in developing-country contexts, remain relatively limited.

Although the findings indicate that EduSmart has potential as an AI-supported adaptive learning tool, several limitations should be considered. The study involved 66 fifth-grade students from three public elementary schools in Bekasi Regency, so the findings cannot yet be generalized

DOI: 10.15408/ tjems.v12i2.46582

to broader primary education contexts. In addition, the use of a one-group pretest–posttest design without a control group means that the increase in students' learning outcomes should be interpreted as preliminary evidence rather than a definitive causal effect of EduSmart. The implementation was also conducted in a limited geographical area, where technological infrastructure, teacher readiness, and students' familiarity with digital learning may differ from other regions. The adaptive logic of EduSmart also relied on a rule-based and decision-tree approach with limited training data; therefore, the accuracy and consistency of the recommendation system still require further testing with larger and more diverse datasets.

These limitations suggest several directions for future research. Further studies should involve larger samples, multiple regions, and stronger research designs, such as quasi-experimental studies with control groups, to provide more reliable evidence of EduSmart's effectiveness. Future development should also expand the application to different subjects and grade levels, improve the transparency and accuracy of the AI recommendation mechanism, and examine the long-term effects of EduSmart on students' motivation, retention, and self-regulated learning. Because the application processes students' learning data, future versions should also include clearer privacy safeguards, parental consent procedures, and transparent data-use policies, especially since the users are elementary school students (UNESCO, 2023). Richer qualitative evidence, such as direct quotations from students and teachers, would also help explain more clearly how EduSmart is used and perceived in real classroom practice.

Conclusion

This study concludes that the EduSmart application, developed through the ADDIE model, has the potential to support adaptive and competency-based learning in primary education. The application integrates quiz-based assessment, competency classification, and learning recommendations in a single platform. Through this system, students' learning data can be used to identify their competency levels and provide follow-up learning activities that are more closely related to their needs. In this sense, EduSmart functions not only as a digital learning application, but also as a classroom support tool that helps teachers understand students' learning difficulties more systematically.

The findings show that EduSmart was considered very feasible by experts, with an average validation score of 4.5 out of 5. Quantitative results also indicated an increase in students' learning outcomes after using the application, with an average N-Gain score of 0.42, which falls into the medium category. Qualitative findings further showed that students responded positively to EduSmart, particularly in terms of ease of use, learning relevance, and motivation. However, because this study used a one-group pretest–posttest design without a control group, the improvement in learning outcomes should be interpreted as preliminary evidence rather than definitive causal evidence of the application's effectiveness.

Theoretically, this study implies that AI-supported adaptive learning can be integrated with competency-based assessment to provide more responsive learning support in Indonesian primary schools. Practically, the findings imply that EduSmart may assist teachers in identifying students

DOI: 10.15408/ tjems.v12i2.46582

who need remedial support or enrichment activities and in planning more differentiated instruction based on learning data. For schools and policymakers, this study suggests that AI-based learning tools can support the implementation of digital transformation and competency-based learning, provided that teacher readiness, infrastructure, and responsible data use are carefully addressed. Future studies should involve larger and more diverse samples, use stronger experimental designs, expand the application to different subjects and grade levels, and improve the transparency and accuracy of the AI recommendation system.

References

Açıkgöz, T., & Babadoğan, M. C. (2021). Competency-based education: Theory and practice. Psycho-Educational Research Reviews, 10(3), 67–95. https://doi.org/10.52963/PERR_Biruni_V10.N3.06

Alamri, H. A. (2021). Learning technology models that support personalization within blended learning environments in higher education. TechTrends, 65(1), 62–78. https://doi.org/10.1007/s11528-020-00530-3

Bhutoria, A. (2022). Personalized education and artificial intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. Computers and Education: Artificial Intelligence, 3, 100068. https://doi.org/10.1016/j.caeai.2022.100068

Bimpeh, Y. (2024). AI-powered adaptive formative assessment: Validity and reliability evaluation. In P. Ilic & R. Casebourne (Eds.), Artificial intelligence in education: The intersection of technology and pedagogy (pp. 127–144). Springer. https://doi.org/10.1007/978-3-031-71232-6_8

Bosch, E., Seifried, E., & Spinath, B. (2021). What successful students do: Evidence-based learning activities matter for students' performance in higher education beyond prior knowledge, motivation, and prior achievement. Learning and Individual Differences, 91, 102056. https://doi.org/10.1016/j.lindif.2021.102056

Branch, R. M. (2009). Instructional design: The ADDIE approach. Springer. https://doi.org/10.1007/978-0-387-09506-6

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Cantú-Ortiz, F. J., Galeano Sánchez, N., Garrido, L., Terashima-Marin, H., & Brena, R. F. (2020). An artificial intelligence educational strategy for the digital transformation. International Journal on Interactive Design and Manufacturing, 14(4), 1195–1209. https://doi.org/10.1007/s12008-020-00702-8

Choi, Y., & McClenen, C. (2020). Development of adaptive formative assessment system using computerized adaptive testing and dynamic Bayesian networks. Applied Sciences, 10(22), 8196. https://doi.org/10.3390/app10228196

Creswell, J. W. (2014). Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.). SAGE Publications.

DOI: 10.15408/ tjems.v12i2.46582

de Hoyos, R., Estrada, R., & Vargas, M. J. (2021). What do test scores really capture? Evidence from a large-scale student assessment in Mexico. World Development, 146, 105524. https://doi.org/10.1016/j.worlddev.2021.105524

Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. American Journal of Physics, 66(1), 64–74. https://doi.org/10.1119/1.18809

Huang, A. Y. Q., Lu, O. H. T., & Yang, S. J. H. (2023). Effects of artificial intelligence-enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. Computers & Education, 194, 104684. https://doi.org/10.1016/j.compedu.2022.104684

Jebb, A. T., Ng, V., & Tay, L. (2021). A review of key Likert scale development advances: 1995–2019. Frontiers in Psychology, 12, Article 637547. https://doi.org/10.3389/fpsyg.2021.637547

Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. Computers and Education: Artificial Intelligence, 2, 100017. https://doi.org/10.1016/j.caeai.2021.100017

Ministry of Education and Culture. (2020). Regulation of the Minister of Education and Culture of the Republic of Indonesia Number 22 of 2020 concerning the Strategic Plan of the Ministry of Education and Culture 2020–2024.

Ministry of Education, Culture, Research, and Technology. (2024). Regulation of the Minister of Education, Culture, Research, and Technology Number 12 of 2024 concerning curriculum at the levels of early childhood education, basic education, and secondary education. https://peraturan.bpk.go.id/Details/281847/permendikbudriset-no-12-tahun-2024

Minn, S. (2022). AI-assisted knowledge assessment techniques for adaptive learning environments. Computers and Education: Artificial Intelligence, 3, 100050. https://doi.org/10.1016/j.caeai.2022.100050

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. Administration and Policy in Mental Health and Mental Health Services Research, 42(5), 533–544. https://doi.org/10.1007/s10488-013-0528-y

Parkavi, R., Karthikeyan, P., & Sheik Abdullah, A. (2024). Enhancing personalized learning with explainable AI: A chaotic particle swarm optimization-based decision support system. Applied Soft Computing, 156, 111451. https://doi.org/10.1016/j.asoc.2024.111451

Rich, J. V., Fostaty Young, S., Donnelly, C., Hall, A. K., Dagnone, J. D., Weersink, K., Caudle, J., Van Melle, E., & Klinger, D. A. (2020). Competency-based education calls for programmatic assessment: But what does this look like in practice? Journal of Evaluation in Clinical Practice, 26(4), 1087–1095. https://doi.org/10.1111/jep.13328

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. International Journal of Educational

DOI: 10.15408/ tjems.v12i2.46582

Technology in Higher Education, 18, Article 54. https://doi.org/10.1186/s41239-021-00292-9

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). Experimental and quasi-experimental designs for generalized causal inference. Houghton Mifflin.

Stefanov, K. (2022). Software systems and frameworks for competency-based learning. Computer, 55(8), 82–88. https://doi.org/10.1109/MC.2022.3148811

Tandika, P. B., & Ndijuye, L. G. (2020). Pre-primary teachers' preparedness in integrating information and communication technology in teaching and learning in Tanzania. Information and Learning Sciences, 121(1/2), 79–94. https://doi.org/10.1108/ILS-01-2019-0009

UNESCO. (2023). Guidance for generative AI in education and research. UNESCO.

Waheed, H., Hassan, S.-U., Aljohani, N. R., Hardman, J., Alelyani, S., & Nawaz, R. (2020). Predicting academic performance of students from VLE big data using deep learning models. Computers in Human Behavior, 104, 106189. https://doi.org/10.1016/j.chb.2019.106189

Yanes, N., Mostafa, A. M., Ezz, M., & Almuayqil, S. N. (2020). A machine learning-based recommender system for improving students' learning experiences. IEEE Access, 8, 201218–201235. https://doi.org/10.1109/ACCESS.2020.3036336

DOI: 10.15408/ tjems.v12i2.46582