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IMPLEMENTATION OF A MACHINE LEARNING-BASED ADAPTIVE LEARNING SYSTEM FOR PERSONALIZING STUDENT LEARNING PATHS

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Abstract

This study addresses the problem of how to design and implement an adaptive learning system to support students in the Modeling and Simulation course, where diverse backgrounds and learning difficulties often hinder the achievement of optimal outcomes. The novelty of this research lies in the integration of a machine learning approach, specifically a Decision Tree Classifier, to personalize students' learning paths based on their pretest performance. The research adopts a Research and Development (R&D) design using the ADDIE model, which consists of five stages: Analysis, Design, Development, Implementation, and Evaluation. Data collection methods included pretest–posttest, questionnaires, and interviews, while data were analyzed both quantitatively to measure learning improvement and qualitatively to capture students' learning experiences. The main results show that the adaptive system effectively categorized students into three distinct learning paths remedial, standard, and enrichment each with tailored content to match students' competencies. The evaluation stage demonstrated an increase in learning outcomes and positive student feedback regarding motivation and satisfaction. These findings indicate that the adaptive learning system not only improved cognitive achievement but also enhanced students' engagement, offering a practical contribution to the development of technology-assisted personalized learning in higher education.

Abstract

Penelitian ini berangkat dari permasalahan bagaimana merancang dan mengimplementasikan sistem pembelajaran adaptif untuk mendukung mahasiswa pada mata kuliah Pemodelan dan Simulasi, di mana latar belakang dan kesulitan belajar yang beragam sering menjadi hambatan dalam mencapai hasil belajar yang optimal. Kebaruan penelitian ini terletak pada integrasi pendekatan machine learning, khususnya Decision Tree Classifier, untuk mempersonalisasi jalur belajar mahasiswa berdasarkan hasil pretest. Penelitian menggunakan desain Research and Development (R&D) dengan model pengembangan ADDIE yang terdiri atas lima tahap: Analisis, Desain, Pengembangan, Implementasi, dan Evaluasi. Metode pengumpulan data meliputi pretest–posttest, angket, dan wawancara, sedangkan analisis data dilakukan secara kuantitatif untuk mengukur peningkatan hasil belajar dan secara kualitatif untuk menggali pengalaman belajar mahasiswa. Hasil utama penelitian menunjukkan bahwa sistem adaptif berhasil mengelompokkan mahasiswa ke dalam tiga jalur belajar remedial, standar, dan pengayaan dengan konten yang disesuaikan dengan kompetensi masing-masing. Tahap evaluasi menunjukkan adanya peningkatan hasil belajar serta respon positif mahasiswa terkait motivasi dan kepuasan. Temuan ini menegaskan bahwa sistem pembelajaran adaptif tidak hanya meningkatkan pencapaian kognitif, tetapi juga memperkuat keterlibatan mahasiswa, sehingga memberikan kontribusi praktis bagi pengembangan pembelajaran personal berbasis teknologi di perguruan tinggi.

INTRODUCTION

Education is the primary foundation for developing a generation capable of facing the challenges of the times. Education must position students as active subjects in the learning process, not simply as objects receiving knowledge. The principle of constructivism asserts that knowledge is constructed through the interaction of individuals with their environment. (Khomarudin & Efriyanti, 2018) (Liza Efriyanti & Annas, 2020) . Therefore, adaptive and personalized learning is part of the effort to realize the essence of education as a humanization process, namely humanizing humans so that they develop according to their individual potential (Bhadriraju, 2019) .

Government policy, enacted through Law Number 20 of 2003 concerning the National Education System, emphasizes that education must be implemented democratically, fairly, and non-discriminatory, while upholding human rights. Furthermore, the Independent Learning–Independent Campus (MBKM) program emphasizes the importance of flexible, student-centered, and individual-needs-based learning. The implementation of an adaptive learning system aligns with this regulatory mandate, as it provides students with opportunities to gain learning experiences that are more relevant to their academic and professional needs (Nurdiyanti, 2024)(Ainissyifa, 2024) .

The importance of learning innovation through the use of technology. Adaptive learning theory emphasizes that each individual has a different learning style, cognitive ability, and comprehension speed (Ezzaim, 2024) . Meanwhile, the development of machine learning technology enables the analysis of student interaction data to provide appropriate material recommendations (Liu, 2022) . Thus, adaptive learning theory and information processing theory underlie the implementation of systems capable of adapting students' learning paths (Wu, 2023) .

Previous research has shown that technology-based adaptive learning can improve student learning outcomes and motivation. For example, an international study demonstrated that machine learning-based systems can reduce dropout rates in complex courses (Mustapha, 2023) . In Indonesia, several similar experiments have also found improved academic achievement when students are provided with learning paths tailored to their individual abilities. This demonstrates that adaptive approaches are more effective than uniform learning.

In the context of the simulation modeling course, students are faced with multidisciplinary material, including mathematical understanding, computer programming, and systems analysis (L Efriyanti et al., 2021) (L Efriyanti et al., 2023) . Variations in student abilities often create gaps in learning outcomes. Adaptive learning systems supported by machine learning are expected to bridge these differences (Pulungan et al., 2025) by providing appropriate content, both in the form of enrichment for high-ability students and remedial for students experiencing difficulties (Purwowidodo, 2018) (Pai, 2021) .

Based on the description above, the implementation of an adaptive learning system not only meets regulatory demands, but also answers the philosophical challenges of education that place students at the center of learning. In addition, this research strengthens empirical evidence that technological innovation is able to provide concrete solutions in improving the quality of learning in higher education.

The aim of this research is to develop and implement a machine learning-based adaptive learning system to personalize student learning paths in a simulation modeling course. This research is expected to produce an innovative learning model that enhances conceptual understanding, improves learning outcomes, and provides a more inclusive and sustainable learning experience for students.

METHODS

This research uses a research and development (R&D) approach with the ADDIE (Analysis, Design, Development, Implementation, Evaluation) development model (Khomarudin & Efriyanti, 2018) (Kardosod, 2023) (Sugihartini & Yudiana, 2018) . Machine learning algorithms, specifically the Decision Tree Classifier, were used in the design phase. The Decision Tree Classifier algorithm was used to classify students studying simulation modeling based on their pretest scores into the learning paths determined by the researchers (Setio et al., 2020) (Liu, 2022) .

The analysis stage is the initial step in identifying student needs in the simulation modeling learning process. The analysis is conducted by mapping the learning difficulties faced by students, analyzing student characteristics, and assessing the gap between existing and expected competencies. Furthermore, the analysis includes a literature review of adaptive learning models and identifying the limitations of available learning media. The results of this analysis form the basis for designing a learning system that suits the needs and characteristics of students.

In the design phase , after needs are identified, the next step is to design the adaptive learning system to be developed. In this phase, researchers develop personalized learning paths tailored to student abilities, determine content structure, and establish adaptation mechanisms using machine learning algorithms. The design also includes the system interface, learning flow, and platform usage scenarios. The primary goal of the design phase is to create a clear conceptual framework so that the development process can be conducted in a focused manner.

Development stage, this stage focuses on realizing the design that has been made into a real product in the form of a web-based learning platform. This system was developed using interactive technology that enables personalized learning paths. Learning content is presented in various formats, such as text, video, interactive quizzes, and case study-based projects. Furthermore, analytics features are developed to monitor individual student progress. At this stage, internal trials are also carried out to ensure the system runs according to design before being implemented.

Implementation stage, after the system is developed, the implementation stage is carried out by applying an adaptive learning platform in the simulation modeling class. Students are directed to use the system as part of their learning activities, either as a companion to face-to-face lectures or as a means of independent learning. Lecturers play a role in facilitating the use of the system, providing direction, and ensuring that each student follows the learning path according to the established categories. This implementation aims to see how the system can function in a real learning context.

The evaluation stage is conducted to assess the effectiveness and quality of the adaptive learning system that has been implemented. Evaluation encompasses two aspects: formative and summative (Magdalena et al., 2020)(Alfafa et al., 2018) . Formative evaluation is conducted throughout the development and implementation process to correct any deficiencies that arise, while summative evaluation is conducted after implementation is complete to assess the achievement of learning objectives. Evaluation methods used include learning outcome tests (pretest–posttest), questionnaires to measure student satisfaction, and interviews to explore learning experiences in more depth. The collected data is then analyzed quantitatively and qualitatively according to research needs.

RESULTS AND DISCUSSION

RESULT

In the analysis phase, initial data were collected from 60 students enrolled in a simulation modeling course. The questionnaire results showed that 65% of students experienced difficulties with basic probability concepts, 50% found programming aspects difficult, and only 25% felt they were able to follow the material well. The average student pretest score was 58.4 with a standard deviation of 12.3, indicating significant variation in students' initial abilities. These findings reinforce the need to design adaptive learning systems that can accommodate differences in understanding levels.

The design stage is shown in Table 1. This research began with identifying needs based on the results of the initial analysis, where variations were found in students' abilities in understanding simulation modeling material. To address these challenges, the Decision Tree Classifier algorithm was chosen due to its ease of implementation, its ability to classify students based on pretest scores, and its clear interpretation in the form of if-then rules. This algorithm is used to design a system capable of grouping students into three learning paths: Path A (Remedial) for scores < 60, Path B (Standard) for scores 60‑79, and Path C (Enrichment) for scores ≥ 80. With this mechanism, the system is expected to provide learning differentiation that is appropriate to the students' initial conditions.

Next, different learning materials and strategies are prepared for each pathway. Pathway A students are given material to reinforce basic concepts, additional videos, and graded practice questions to improve basic understanding. Track B students follow a standard syllabus with reinforcement in the form of formative quizzes to practice understanding of important concepts. Meanwhile, Track C students are directed towards real-world case-based projects and advanced literature studies to gain a more complex and contextual learning experience. To ensure its effectiveness, each path is equipped with an automated evaluation system that provides immediate feedback. The results of this evaluation are used as a basis for updating material recommendations and allowing students to change paths if there is significant progress in their learning outcomes.

Table 1. Adaptive Learning System Design Stages

Step	Activities Carried Out	Expected results
1. Identify Needs	Collecting data on student difficulties through questionnaires & pretests	Student initial ability profile
2. Algorithm Determination	Selecting *a Decision Tree Classifier* as the basis for an adaptive system	Student classification model based on performance
3. Learning Path Design	Create criteria for paths A, B, C based on pretest scores	Division of learning paths according to ability
4. Preparation of Materials	Organize content according to the path (remedial, standard, enrichment)	Learning materials that are relevant to student needs
5. Evaluation & Feedback	Determine quiz methods, formative tests, and *real-time feedback*	Dynamic scoring system that enables continuous personalization

Development phase, the web-based system was then developed with an interactive simulation modeling learning module as shown in Figure 1. Track A students get access to videos made by the simulation modeling lecturer in the form of additional explanations and tiered practice questions. Track B students are facilitated with formative quizzes to reinforce concepts (statistics, calculus and programming logic), while Track C students are given a simulation modeling project assignment based on a case study in the field in the form of data collection, data processing, designing models from data obtained in the field, making reports and presentations of results and making draft articles to be submitted to relevant journals. Activity log data shows that Track A students access the material an average of 8 times per week, higher than Track C students who average only 4 times per week. This difference indicates that students with lower abilities are more active in seeking additional material through the system.

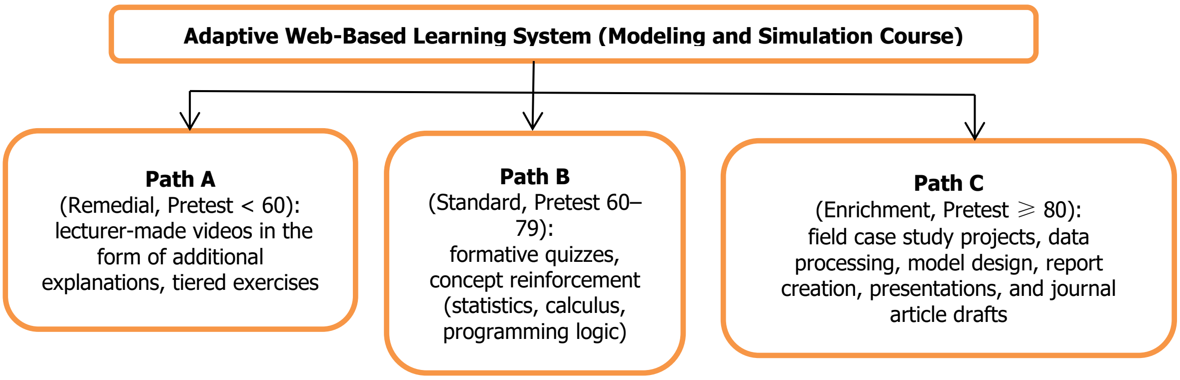

Figure 1. Adaptive Web-Based Learning System for Modeling and Simulation Course

Implementation stage, the system was implemented for 16 meetings in one semester. The average pretest score of students was 58.4 , while the average posttest score increased to 77.6 with a standard deviation of 10.1. This increase indicates a significant improvement in mastery of the material. The calculation of normalized gain (g) shows that most students experienced an increase in the medium category (28 students, 46.7 %), the low category (28 students, 46.7%), and only a small portion in the high category (4 students, 6.6%) as visually seen in figures 2 and 3.

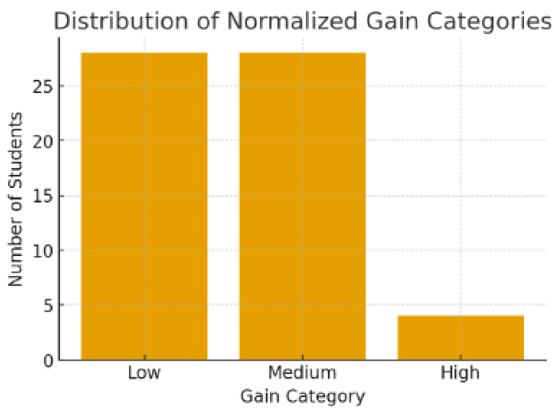

Figure 2. Number of Students in the Simulation Modeling Course in Each Category (Low, Medium, High) After Implementing the Adaptive Web-Based Learning System

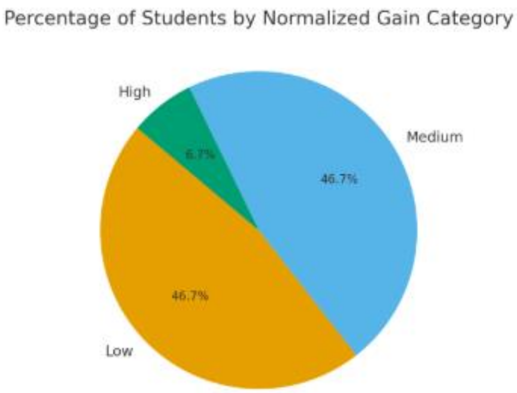

Figure 3. Percentage Distribution of Students in the Simulation Modeling Course Based on the Normalized Gain Category After Implementing the Adaptive Web-Based Learning System

Evaluation Stage, quantitative evaluation was conducted using a paired sample t-test, and the results showed that there was a significant difference between the pretest and posttest scores (p-value <0.05) . This proves that the adaptive learning system is effective in improving student learning outcomes. Qualitative evaluation through a questionnaire showed that 82% of students felt the system helped their understanding, 76% felt their learning motivation increased, and only 10% experienced technical problems. Thus, the evaluation concluded that this system not only improves learning outcomes but also increases student satisfaction with the learning process.

DISCUSSION

This study aims to answer the challenges related to the heterogeneity of student competencies in the Simulation Modeling course and to answer whether a machine learning-based adaptive learning system can improve student learning outcomes and learning satisfaction. The findings of this study provide strong evidence that the system successfully addresses the problem formulation. A significant increase from pretest to posttest scores, validated through a paired sample t-test, indicates that the adaptive learning path based on pretest scores can substantially improve material mastery. Furthermore, students' positive responses regarding their learning experience also confirm the system's effectiveness, not only from a cognitive perspective but also in terms of motivation and affective engagement.

The results of this study were obtained through the systematic application of the ADDIE model, where the analysis stage successfully identified the main difficulties in learning, the design stage utilized the Decision Tree Classifier to classify students (Setio et al., 2020) (Ramadhani et al., 2024) , and the development phase resulted in distinct learning modules for each pathway. This structured approach allowed for consistent implementation across 16 meetings, while the evaluation phase combined quantitative and qualitative data. This methodological rigor ensures that the results obtained are not accidental, but rather the consequence of deliberate design and implementation.

Interpretation of the findings suggests that adaptive learning provides substantial benefits for students of varying ability levels. Students on the remedial track (Track A) were shown to be more active users of the system, as reflected by higher activity logs, indicating greater effort to overcome learning difficulties. Meanwhile, students on the enrichment track (Track C) were challenged through project-based assignments, in line with the principle of differentiated instruction, which ensures that high-ability students are still facilitated with relevant challenges. The distribution of gains, dominated by low and medium categories, also shows that although the system is able to improve the learning outcomes of the majority of students, further refinement is needed to enable more students to reach the high categories.

When linked to existing theoretical frameworks, this research reinforces Vygotsky's Zone of Proximal Development (ZPD) concept (Iba, 2019) , where providing adaptive scaffolding can help students exceed their competency levels. The use of machine learning as a classifier aligns with learning analytics literature that emphasizes the importance of predictive models in personalized learning. In addition, increased student motivation and satisfaction are in line with self-determination theory, which emphasizes the role of autonomy and competence in fostering intrinsic motivation.

Furthermore, this research also offers a modified framework for adaptive learning in higher education. By integrating simple yet transparent decision tree-based classification with differentiated learning content presentation, this research provides a practical model that bridges traditional instructional design (ADDIE) with data-driven personalization. This contribution can be seen as part of the development of AI-based adaptive learning models that emphasize transparency and understandability, making them more readily accepted in academic environments.

Thus, this study demonstrates that a carefully designed web-based adaptive learning system can reduce learning gaps, increase student motivation, and provide a replicable framework for personalizing education in higher education. These findings underscore the importance of not only the use of technology but also its integration with sound pedagogical theory. A key contribution of this research is that it offers a replicable model in other institutions and paves the way for the future development of adaptive systems that incorporate transparency, interpretability, and the specific needs of learning domains.

CONCLUSION

This study concludes that a web-based adaptive learning system designed using the ADDIE model and supported by the Decision Tree Classifier algorithm has proven effective in improving student learning outcomes in the Simulation Modeling course, as indicated by a significant increase in posttest scores, a majority of normalized gains in the medium category, and high levels of student satisfaction and motivation. This system successfully accommodates differences in ability levels by providing appropriate learning paths, although improvements are still needed to enable more students to reach the high improvement category. Therefore, it is recommended that further development integrate more dynamic adaptation features with real-time learning analytics support, expand the variety of interactive content, and strengthen technical and pedagogical support so that the system can be implemented more widely in various courses and higher education institutions.

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