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RESEARCH ARTICLE

Optimizing Problem-Solving in Technical Education: An Adaptive Learning System Based on Artificial Intelligence

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ABSTRACT The increasing complexity of educational challenges in technical disciplines highlights the need for personalized learning systems to address diverse student needs. Traditional methods, often relying on static activities or predefined rules, limit their ability to adapt to individual progress, hindering the development of critical skills such as problem-solving. Based on rules or machine learning, existing adaptive systems offer varying levels of personalization and efficiency but face significant scalability and computational demand barriers. This study proposes an adaptive learning system powered by deep learning algorithms designed to optimize problem-solving skills in technical college students. The system dynamically adjusts the difficulty of activities based on real-time performance data, ensuring a personalized and practical learning experience. A controlled experimental study was conducted with 200 students over eight weeks, divided into pretest, intervention, and posttest phases. The experimental group, which used the adaptive system, showed a 14% improvement in precision (from 71.8% to 85%) compared to 5% for the control group. In addition, the experimental group reduced its average time per activity by 15%, achieving 105 seconds compared to 124 seconds for the control group. These results demonstrate the system's ability to improve precision, efficiency, and motivation in problem-solving tasks. By balancing computational efficiency with high personalization, this proposal offers a scalable and innovative solution that responds to current limitations in adaptive learning technologies.

INDEX TERMS Adaptive learning, problem-solving, artificial intelligence in education, learning personalization.

I. INTRODUCTION

The transformation of educational systems has been a central theme in recent decades, driven by the need to meet the demands of a world in constant technological evolution [1]. Artificial intelligence (AI) has emerged as a key tool to personalize learning and enhance the development of fundamental skills in students, such as problem-solving [2]. Educational personalization, the ability to adjust learning activities to individual needs dynamically, has proven effective in optimizing academic performance and student motivation [3]. However, despite significant advances in the design of adaptive systems, many face limitations related to scalability, computational efficiency, and integration into diverse educational contexts [4].

This study addresses these limitations by developing and implementing an AI-based adaptive system designed to optimize problem-solving skills in a university environment. Unlike traditional approaches, which rely on static activities or predefined rules, the proposed system uses advanced deep

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learning algorithms to dynamically adjust the difficulty of activities based on individual student performance [5]. This approach ensures that each participant receives personalized learning, promoting better performance and a more satisfying and motivating educational experience.

Problem-solving is an essential skill in training students in technical disciplines, as it is directly related to their ability to analyze complex situations, propose solutions, and make informed decisions [6]. However, traditional teaching methods, which often rely on homogeneous activities, do not always succeed in meeting individual learning needs. Previous research, such as that conducted by Quintanar-Casillas and Hernández-López [7] and Essa et al. [8], has shown that static or rule-based systems present significant limitations in adapting to the diversity of students' skills and learning paces.

On the other hand, more recent studies, such as those by Nasser Al-Mhiqani et al. [9], have explored integrating machine learning models into adaptive systems, showing substantial improvements in personalization and efficiency. However, these approaches are often highly computationally demanding, making them difficult to implement in resource-constrained educational environments. In this context, systems that combine a high level of customization with operational efficiency must be developed to allow for scalability and adoption in various educational contexts [10].

The system developed in this study responds to this need, offering an innovative solution that balances customization and efficiency. Furthermore, it was explicitly designed to address problem-solving skills, a critical area in technical and vocational education, where students' ability to face complex challenges broadly defines their academic and professional success.

An experimental study was conducted with 200 university students from a technical faculty to evaluate the system's effectiveness. The participants were divided into a control group, which used traditional learning methods, and an experimental group, which interacted with the adaptive system. Performance evaluation was carried out in three stages: pretest, intervention, and posttest, using key metrics such as response precision, average time taken, and number of attempts.

The adaptive system that was developed integrates neural network algorithms to adjust the difficulty of educational activities dynamically. These networks process data in real-time, allowing immediate feedback that optimizes the student learning experience [11]. In addition, qualitative analysis tools were used to capture students' perceptions about ease of use, relevance of activities, and the system's impact on their motivation and learning [12].

This study represents a significant advance in integrating AI into adaptive learning systems, demonstrating that it can effectively combine personalization and efficiency. Its contributions improve student performance metrics and offer a scalable and accessible model for educational institutions with different technological capabilities. Furthermore, by focusing on problem-solving skills, the system responds to a critical need in training technical and scientific professionals. In a landscape where personalized education is increasingly relevant, this study provides a practical and effective solution that has the potential to transform current teaching approaches and set a new standard for AI-powered adaptive learning.

This article is organized as follows: Section II presents a comprehensive literature review focusing on previous research on adaptive learning systems and their key characteristics. Section III describes the methodology employed, detailing the development and implementation of the AI-based adaptive system. Section IV discusses the results obtained, highlighting the system's impact on personalization, efficiency, and student performance. Finally, Section V and VI concludes the study by summarizing the main findings, discussing limitations, and proposing directions for future research.

II. LITERATURE REVIEW

The scientific literature has explored various approaches to personalizing educational experiences in adaptive learning systems, highlighting differences in customization levels, processing efficiency, and their impact on problem-solving skills. However, direct comparisons of metrics such as processing times or precision are often irrelevant unless the same problem, dataset, and hardware are used. Instead, this section focuses on the methodological contributions and their alignment with the proposed system's goals.

Quintanar-Casillas and Hernández-López [7] presented a rule-based approach to personalize educational activities. While this system achieves moderate customization, its reliance on predefined rules limits adaptability to real-time student progress. In contrast, our system employs AI-driven adaptive algorithms, enabling dynamic adjustments to be more responsive to individual performance and learning trajectories.

Wang et al. [13] introduced a machine learning-based adaptive system capable of real-time adjustments to educational activities, showcasing significant advancements in personalization. Nevertheless, the high computational cost of this system restricts its applicability in resource-constrained environments. Our proposal addresses this challenge by optimizing AI models to balance computational efficiency with high levels of personalization, making the system more accessible to institutions with diverse technological capabilities.

Adel and Dayan [14] explored a static approach using predefined educational activities, prioritizing simplicity but offering limited personalization. While effective in contexts where operational simplicity is paramount, this approach struggles to address the dynamic needs of learners. By leveraging real-time data analysis, our system ensures that activities remain relevant and progressively challenging, avoiding the stagnation inherent to static systems.

The proposed adaptive learning system distinguishes itself by its ability to adjust AI-based activities, ensuring scalability and real-time responsiveness dynamically. Rather than relying on isolated performance metrics, this work emphasizes methodological innovations that allow personalized and efficient learning experiences across diverse educational contexts.

III. MATERIALS AND METHODS

A. STUDY DESIGN

This study design combines qualitative and quantitative approaches, adopting a mixed method that analyzes objective metrics from student performance and subjective perceptions obtained through data collection tools [15], [16]. This approach was selected to ensure a comprehensive understanding of the effects of implementing the AI-based adaptive learning system on developing problem-solving skills.

The population studied focuses exclusively on university students, considering their advanced level of critical reasoning and the need to strengthen key competencies for their professional development. The selection of this educational level allows for applying problems of greater complexity linked to real situations in specific disciplines, increasing the system's relevance and ability to promote meaningful learning.

The study's main objective is to design, implement, and evaluate an adaptive learning system that uses advanced AI algorithms to personalize activities and feedback based on individual student performance. This system is characterized by its ability to analyze learning patterns and dynamically adjust the difficulty and focus of the proposed activities. The second goal is to evaluate the impact of this implementation using quantitative and qualitative indicators, such as precision in problem-solving, time spent on activities, and student's perception of the system's usefulness in their training process.

To ensure adequate measurement of the results, the study includes differentiated phases, from an initial assessment of student's skills to implementing the system in a controlled environment and a subsequent impact assessment. The corresponding subsections describe these stages, highlighting how specific algorithms, techniques, and data are integrated into each process.

B. PLATFORM AND TECHNOLOGIES USED

1) LEARNING PLATFORM

The adaptive learning system is built on Moodle, version 4.2, and was selected for its modular architecture that allows customization through plugins and extensions. Moodle is the primary environment for managing educational activities, storing student interaction data, and providing real-time adaptive feedback [17]. To integrate Moodle functionalities with the AI algorithms designed in this work, a custom API called Learning Adaptation Interface (LAI) is implemented. This API is developed using Flask in Python, an efficient framework for handling HTTP requests, and is deployed within a Docker container to ensure portability and scalability.

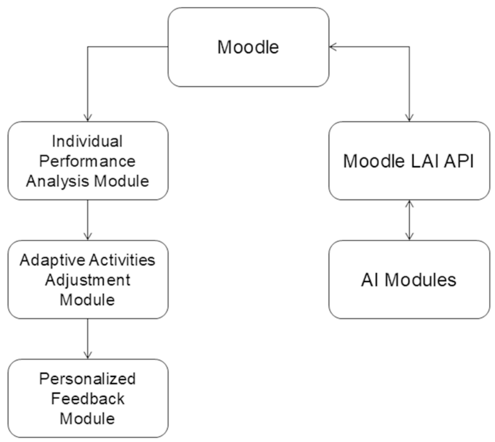

FIGURE 1. System architecture diagram showing integration between moodle, the LAI API, and AI modules.

The LAI API is an intermediary between Moodle and the AI modules hosted on external servers. Data collected from Moodle, including student responses, times spent on activities, and interaction patterns extracted from event logs, are transmitted through secure endpoints protected with JSON Web Tokens (JWT). AI models process These data in real-time, enabling dynamic adjustments and personalized customization of educational activities. This integration transforms Moodle from a static learning management system into an active platform for personalized education [18].

In addition to the API, custom modules are developed within Moodle to enhance its functionality. The Individual Performance Analysis Module collects and analyzes data on the precision of answers, the time spent solving problems, and the number of attempts made. This analysis uses statistical algorithms implemented with NumPy and generates interactive graphical reports using Matplotlib [19]. These reports are accessible to both students and teachers, offering detailed progress monitoring and identifying specific areas for improvement. Furthermore, the Adaptive Activities Adjustment Module utilizes the processed data to generate dynamic activities through JSON templates customized to each student's skill level. The Personalized Feedback Module employs natural language processing models to create detailed and personalized explanations, delivered in text or audio format using Google Text-to-Speech [20].

To comprehensively understand the system's architecture, Figure 1 presents a diagram illustrating the interactions between Moodle, the custom API, and the AI modules. The diagram highlights the flow of data, from its collection in Moodle to its processing by the AI models and the subsequent adjustments and feedback provided to students. This visualization clearly depicts how the components integrate seamlessly to achieve a dynamic and adaptive learning experience.

2) ARTIFICIAL INTELLIGENCE TECHNOLOGIES

The system employs deep learning and machine learning algorithms to analyze educational data and generate personalized activities, integrating these technologies into a robust and scalable architecture. Recurrent Neural Networks (RNNs) are configured to process temporal data streams, capturing the sequential nature of students' interactions. Specifically, a Long Short-Term Memory (LSTM) variant manages the long-term dependencies in tracking students' progressive performance over time. The RNNs are trained with a batch size of 128, using the Adam optimizer with an initial learning rate of 0.001. The input features include time-stamped activity logs, success rates, and interaction durations, normalized to improve convergence during training.

The Bidirectional Encoder Representations from Transformers (BERT) model is fine-tuned to analyze and understand students' natural language responses. The pre-trained "bert-base-uncased" model from Hugging Face is utilized, with additional training conducted on domain-specific educational data to improve the contextual understanding of student feedback. The fine-tuning involves a maximum sequence length of 512 tokens, a learning rate 2e-5, and a training duration of 10 epochs, ensuring the model adapts to educational contexts.

TensorFlow is employed to create scalable neural network architectures optimized for distributed training across multiple GPUs. Training pipelines leverage TensorFlow's 'tf.distribute.MirroredStrategy' to parallelize computations, reducing training time and ensuring efficient resource utilization. PyTorch is selectively used for experiments with convolutional neural networks (CNNs) designed to analyze interactive graphical resources, providing flexibility in model experimentation.

Data collected from student interactions is processed using 'pandas' for data cleaning and aggregation and 'NumPy' for numerical transformations. Features such as time spent on tasks, the number of attempts, and precision rates are scaled to a range of [0, 1] using min-max normalization. This preprocessing ensures that all inputs are standardized, reducing the risk of bias in model predictions.

The OpenAI API is employed for advanced natural language processing tasks. Adaptive explanations and feedback are generated by fine-tuning the prompts to align with the student's performance metrics. For example, GPT-4 is utilized with a temperature setting of 0.7 to balance creativity and coherence in feedback generation. The integration ensures personalized explanations address specific learning gaps while maintaining clarity and engagement.

This configuration ensures high accuracy and relevance in adaptive activities and enables the system to process and respond to real-time educational data effectively. Combining fine-tuned models and robust data pipelines ensures a seamless and scalable implementation tailored to diverse educational contexts.

3) COMPUTING INFRASTRUCTURE

The system operates on a high-performance server with two Intel Xeon Platinum 8260 processors, each featuring 24 cores and a base frequency of 2.4 GHz. This configuration provides sufficient computational power to manage multiple simultaneous tasks. The server also includes 512 GB of DDR4 RAM, ensuring the ability to process large volumes of data in real-time without delays.

Deep learning models are trained using two NVIDIA A100 Tensor Core GPUs with 80 GB of HBM2 memory each, connected via an NVLink bus to enhance data transfer speeds between GPUs. A hybrid system is employed for storage, consisting of a RAID 5 array of SATA hard drives with a total capacity of 10 TB for long-term storage and 4 TB NVMe solid-state drives for fast access to active datasets.

Students interact with the system using personal devices, such as laptops or tablets, that meet minimum specifications, including an Intel Core i5 processor (or equivalent ARM-based processor for specific devices like iPads with M-series chips), 8 GB of RAM, and a stable internet connection with a minimum speed of 10 Mbps. Examples of compatible tablets include the Microsoft Surface Pro 9, which offers configurations with Intel Core i5 or i7 processors and ARM-based SQ3 variants, ensuring compatibility with Windows-based applications. Similarly, the Apple iPad Pro, equipped with M1 or M2 chips and 8 GB of unified memory, provides high-performance capabilities and compatibility with advanced educational applications. Another viable option is the Samsung Galaxy Tab S9, featuring Snapdragon 8 Gen 2 processors and up to 12 GB of RAM, which supports multitasking and interactive activities with robust performance.

These devices are selected based on their ability to meet the system's requirements while offering flexibility and portability for students. Their support for advanced features, such as touch interaction and stylus input, enhances the educational experience. The infrastructure accommodates diverse user preferences by ensuring compatibility with a range of devices while maintaining the necessary performance standards.

To support seamless interaction, the system relies on a 1 Gbps fiber optic link connecting the central server to student devices, enabling real-time data transfer and interaction. A network redundancy system, incorporating load balancers and mirror servers, ensures uninterrupted availability, even in the case of server or connection failures. This comprehensive infrastructure guarantees a stable, scalable, and efficient environment for adaptive learning applications.

C. POPULATION AND SAMPLE

The study was conducted on a technical university faculty with approximately 1,200 students enrolled. A segmented sample was selected based on relevant demographic and academic criteria to ensure representative and controlled results, following methodologies commonly applied in similar educational studies.

1) DESCRIPTION OF PARTICIPANTS

The sample includes 200 students randomly selected from different faculty academic programs. This sample size is determined using a 5% margin of error and a 95% confidence level, ensuring adequate representation of the total population. The students are between 18 and 25 years old, with an average age of 21, and come from electronic engineering, computer systems, and mechatronics programs. Segmenting the sample by area allows us to evaluate the system's impact in academic contexts related to resolving technical problems.

Regarding inclusion criteria, students enrolled in at least one subject that requires applying technical problem-solving skills, such as circuit analysis, advanced programming, or integrated systems design, are selected. In addition, participants must have access to personal devices that meet the system's technical requirements, such as laptops or tablets with stable connectivity. On the other hand, students who cannot guarantee continuous participation throughout the experiment or have previous experience with adaptive learning tools based on AI are excluded from the study to avoid bias in the results.

2) GROUP DIVISION

The selected sample consists of 200 students divided into two groups of 100 students each. The assignment to these groups is done randomly to minimize potential biases and ensure comparability. The control group follows traditional learning methods, relying on teacher-student interaction and static resources such as guides and digital books. In this group, educational activities and assessments remain uniform and are not adapted based on individual student performance.

The experimental group utilizes the AI-based adaptive learning system developed in this study. This system dynamically adjusts educational activities based on each student's progress and performance, providing personalized feedback and adaptive resources to enhance problem-solving skills. Students in this group access the system through the Moodle platform, which records all interactions and generates real-time data for subsequent analysis.

Both groups participate in the same core academic activities, ensuring a consistent basis for comparison. However, the adaptive capabilities of the experimental group's system introduce a significant variable, allowing for an evaluation of its impact in contrast to traditional methods. Key metrics analyzed include precision in problem-solving, the time required for each activity, and students' subjective assessment of the system's effectiveness.

D. DEVELOPMENT OF THE ADAPTIVE LEARNING SYSTEM

1) SYSTEM ARCHITECTURE

The adaptive learning system has a modular architecture integrating several interconnected stages, each with a specific function within the learning flow. In the data entry stage, real-time information is collected from the Moodle platform. This information includes parameters such as student responses to activities, the time spent solving problems, the number of attempts, and general interactions within the platform.

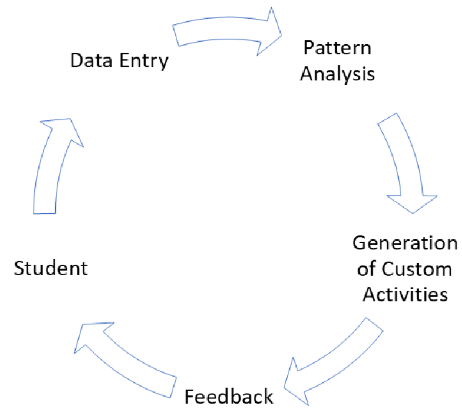

FIGURE 2. Adaptive learning system architecture flowchart.

Once collected, the data is processed in the pattern analysis module. This module uses machine learning algorithms to identify relevant trends and patterns in student performance, allowing for a detailed assessment of individual strengths and areas for improvement. The results at this stage feed into the custom activity generation module, where tasks are created and dynamically adjusted to each student's skill level. These activities are generated using adaptive templates parameterized according to the analysis results.

Finally, the feedback module is responsible for providing detailed information to the student about their progress, highlighting areas of success, and offering specific recommendations to improve their performance in critical areas. This module uses natural language processing models to create textual explanations and, when necessary, convert them to audio using speech synthesis tools. The complete flow of information between these modules is represented in Figure 2.

2) CUSTOMIZED ADAPTATION

The system dynamically adjusts the difficulty of activities based on the Adjusted Difficulty Index (ADI), which serves as the primary metric for tailoring educational experiences. This index evaluates student performance parameters, including the percentage of recent correct answers (E), the average time spent solving problems (T), and the number of attempts required to complete a task (I). These variables are combined in the following equation:

$$ADI = \alpha \cdot E + \beta \cdot \left(\frac{1}{T}\right) + \gamma \cdot \left(\frac{1}{I}\right) \tag{1}$$

The coefficients α, β, and γ represent weights assigned to each variable and are calibrated during the system's development phase to achieve an optimal balance between accuracy, efficiency, and persistence. These coefficients are determined using grid search optimization over a pilot dataset of 10,000 interaction records, ensuring that the ADI accurately reflects performance trends.

The difficulty of the current activity is evaluated in real-time using data collected during its completion. After the task is finished, the ADI index is recalculated. If the ADI exceeds 0.8, the next activity assigned is more challenging. If the index is below 0.5, the system selects a more straightforward activity to reinforce foundational concepts. For values between 0.5 and 0.8, the system maintains the current difficulty level to provide a consistent challenge.

Implementing this dynamic adjustment is supported by artificial intelligence models that process real-time data and provide actionable outputs. Recurrent neural networks, precisely LSTM networks, are used to process data streams such as activity completion times, success rates, and attempts, capturing temporal dependencies crucial for accurate predictions. These models are trained using TensorFlow with the Adam optimizer, a learning rate of 0.001, and a batch size of 128. The training dataset is split into 80 percent for training and 20 percent for validation to ensure model generalization. Transformer models, such as BERT (Bidirectional Encoder Representations from Transformers), are fine-tuned to analyze natural language responses. The fine-tuning process involves training on domain-specific educational data for ten epochs, using a sequence length of 512 tokens and a learning rate 2e-5. This enables the system to classify and interpret student feedback effectively, ensuring that adaptive activities align with the learning context.

A REST API integrates the Adjusted Difficulty Index calculation with the Moodle platform. This API retrieves interaction data, preprocesses it using pandas and NumPy for feature extraction and normalization, and passes it to the AI models for analysis. The models' output determines the difficulty level of the next activity, which is then dynamically updated in Moodle. The system also uses a dynamic algorithm for difficulty adjustment, which is structured as follows:

Algorithm 1 Dynamic Adjustment of Activity Difficulty

Require: Historical student data (*student_history*), parameters α, β, γ
Ensure: Adjusted difficulty level for the next activity

Initialize α, β, γ
Define `calculate_ADI(hits, time, attempts):`
  $ADI \leftarrow \alpha \cdot hits +$
  $\beta \cdot \left(\frac{1}{time}\right) +$
  $\gamma \cdot \left(\frac{1}{attempts}\right)$
  return *ADI*
Define `adjust_difficulty(student_history):`
  $hits \leftarrow$
    `calculate_hit_percentage(`
    `student_history)`
  $time \leftarrow$
    `calculate_average_time(`
    `student_history)`
  $attempts \leftarrow$
    `calculate_failed_attempts(`
    `student_history)`
  $ADI \leftarrow$ `calculate_ADI`$(hits, time, attempts)$
if $ADI > 0.8$ **then**
  Increase activity difficulty
else if $ADI < 0.5$ **then**
  Reduce activity difficulty
else
  Maintain current difficulty
end if

The system is deployed on a high-performance server with two NVIDIA A100 GPUs, each with 80 GB of HBM2 memory and two Intel Xeon Platinum 8260 processors with 512 GB DDR4 RAM. Training pipelines are parallelized using TensorFlow's mirrored strategy to optimize GPU utilization, reducing training time while maintaining model accuracy. This implementation ensures that each student's learning path is dynamically adjusted based on their real-time performance, fostering personalized learning experiences. By providing detailed documentation of the AI models, training parameters, data preprocessing, and system architecture, this methodology is fully replicable for researchers with similar resources, ensuring scientific rigor in its application.

3) DATA ANALYSIS METHODS

An analysis based on correlations between student performance variables is performed to identify strengths and areas for improvement. The system builds an RR correlation matrix, defined as:

$$R_{ij} = \frac{\mathrm{Cov}(X_i, X_j)}{\sigma_{X_i} \cdot \sigma_{X_j}} \tag{2}$$

In this equation, X_i and X_j represent individual performance variables, such as precision in specific activities or time spent solving them. The covariance between these variables is denoted as $\mathrm{Cov}(X_i, X_j)$, while σ_{X_i} and σ_{X_j} are their respective standard deviations. The values in the correlation matrix are interpreted to identify areas where students consistently underperform, indicating potential weaknesses.

The analysis also uses linear regression to predict the impact of specific interventions on student performance. The regression equation is defined as:

$$Y = \beta_0 + \sum_{k=1}^{n} \beta_k \cdot X_k \tag{3}$$

Here, Y represents the target variable, such as overall performance, and X_k is the predictor variable related to completed activities. The coefficients β_k indicate the relative contribution of each predictor.

E. EXPERIMENTAL PROCEDURE

The experimental procedure is developed in three well-defined stages: pretest, educational intervention, and posttest. These stages are structured sequentially to evaluate the adaptive system's impact on developing problem-solving skills [24], [25].

1) PRETEST STAGE

The pretest aims to establish a baseline of students' problem-solving skills. To do so, a set of standard activities is designed, including technical problems related to electronic engineering, computer systems, and mechatronics. These activities are carefully selected to avoid biases related to specific prior knowledge and ensure that they assess general skills such as analysis, synthesis, and creativity.

The pretest is administered simultaneously to students in both the control and experimental groups, using the Moodle platform to standardize the assessment conditions. Metrics collected during this stage include the percentage of correct answers, the time spent on each activity, and the number of attempts required. These data are processed using normalization techniques to ensure comparability between participants and serve as an initial reference for subsequent analysis.

2) EDUCATIONAL INTERVENTION

In this stage, the adaptive learning system is implemented in the experimental group over eight weeks. Students interact with the system using the Moodle platform, where activities are dynamically adapted to their skill levels [25]. The system adjusts the difficulty of the activities based on data collected in real time, using the ADI as the primary metric. Personalized feedback is provided after each interaction, guiding students through their learning process and ensuring continuous engagement.

The difficulty of each activity is predefined during the system design phase based on a rigorous analysis of educational content and its associated complexity. Activities are classified into difficulty levels by considering factors such as the cognitive load required, the number of logical steps involved, and the typical performance of students at a given skill level. Activities are initially validated by subject matter experts and tested in pilot groups before being integrated into the system to minimize errors in assigning difficulty levels. This ensures the classification aligns with the intended learning outcomes and student capabilities.

The system continuously recalibrates the ADI thresholds during the intervention for the experimental group, ensuring that difficulty adjustments remain accurate and responsive to real-time performance data. This recalibration is achieved by analyzing aggregate performance trends and correcting for any biases introduced by individual activities or variations in student behavior. In parallel, the control group continues to use traditional learning methods. This group accesses the same base activities as the experimental group but without the system's adaptive capabilities. The activities in the control group are static and do not adjust based on individual student performance, and the feedback provided is generalized and lacks personalization.

During this period, data are continuously collected from both groups. For the experimental group, these data include detailed metrics from the adaptive system, such as ADI values, interaction patterns, and activity completion rates. For the control group, the collected data are limited to the outcomes of standard activities and general interaction metrics with the available educational resources. This comprehensive data collection ensures that the impact of the adaptive learning system can be rigorously compared to traditional methods, providing valuable insights into its effectiveness and areas for improvement.

3) POSTTESTING STAGE

At the end of the intervention period, a posttest designed to assess changes in problem-solving skills is administered. This assessment uses a set of activities equivalent to the pretest, maintaining the same structure and difficulty level to ensure comparability. The posttest is carried out under the same standardized conditions for both groups, again using Moodle as the assessment platform.

The metrics collected at this stage include the same variables as in the pretest, such as the percentage of correct answers, the time spent, and the number of attempts. In addition, additional indicators are calculated, such as the relative improvement in each metric and the level of consistency in performance during the activities.

F. DATA ANALYSIS

The study's data is analyzed using robust statistical methods and advanced data processing techniques. This analysis includes assessing significant differences between groups, determining the correlation between system use and improving specific skills, and processing qualitative data from surveys.

1) STATISTICAL METHODS

Statistical analysis focuses on determining whether there are significant differences between the control and experimental groups in terms of performance in problem-solving skills. For this purpose, independent samples t-tests and analysis of variance (ANOVA) are used [26].

The independent samples t-test is applied to assess significant differences in key metrics such as percentage of correct answers (E), average time taken (T), and number of attempts (I) between the groups. The t-test equation is:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{4}$$

where:

- $\overline{X}_1$ and $\overline{X}_2$ are the means of the metrics in the experimental and control groups.
- s_1^2 and s_2^2 are the variances of the groups.
- n_1 and n_2 represent the sample sizes.

ANOVA analysis evaluates interactions between multiple factors, such as time, difficulty, and feedback in the experimental group. The general ANOVA model is expressed as:

$$Y_{ij} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ij} \tag{5}$$

where:

- Y_{ij} is the observed response variable.
- μ is the overall mean.
- α_i represents the effect of the difficulty level.
- β_j corresponds to the effect of the interaction time.
- $(\alpha\beta)_{ij}$ is the interaction between the factors.
- ϵ_{ij} is the error term.

In addition, correlations between system usage and improvement in specific skills are assessed using the correlation matrix. The correlation between two variables X and Y is calculated as:

$$r = \frac{\mathrm{Cov}(X, Y)}{\sigma_X \cdot \sigma_Y} \tag{6}$$

where:

- $\mathrm{Cov}(X, Y)$ is the covariance between X and Y.
- σ_X and σ_Y are the standard deviations of X and Y, respectively.

2) PROCESSING TECHNIQUES

To visualize the quantitative results, bar and line graphs show variable trends such as the percentage of correct answers and time taken. These graphs are built using the Matplotlib and Seaborn libraries and are designed to highlight differences between groups over time. The equation for generating trend values in line graphs is based on simple linear regression:

The linear regression model is expressed as:

$$Y = \beta_0 + \beta_1 X + \epsilon \tag{7}$$

where:

- Y is the dependent variable (e.g., percentage of correct answers).
- X is the independent variable (e.g., time in weeks).
- β_0 and β_1 are the regression coefficients.
- ϵ is the error term.

The qualitative data analysis of the surveys is performed using natural language processing (NLP) tools [27]. The texts are processed to identify keywords and associated sentiments using the Term Frequency-Inverse Document Frequency (TF-IDF) model, which is defined as:

$$\text{TF-IDF}(t, d, D) = \mathrm{TF}(t, d) \cdot \mathrm{IDF}(t, D) \tag{8}$$

where:

- $\mathrm{TF}(t, d)$ is the frequency of the term t in document d.
- $\mathrm{IDF}(t, D) = \log\left(\frac{|D|}{1+|\{d \in D : t \in d\}|}\right)$, where $|D|$ is the total number of documents, and $|\{d \in D : t \in d\}|$ is the number of documents containing the term t.

G. ETHICAL CONSIDERATIONS

The study's development and execution are carried out under strict ethical guidelines that guarantee respect for participants' rights and data protection. These measures ensure that the study complies with the ethical standards applicable to research in educational settings.

1) INFORMED CONSENT OF PARTICIPANTS

Before participating, all study participants receive detailed information about the project's objectives, procedures, and scope. This information includes a description of the activities to be carried out, the duration of the study, and the data to be collected during the different stages. To formalize their participation, each student signs an informed consent form, highlighting that their participation is entirely voluntary and that they are free to withdraw without academic or personal repercussions. In addition, it is clarified that the data collected will be used exclusively for research and analysis purposes.

2) GUARANTEES OF PRIVACY AND ANONYMIZATION OF THE DATA COLLECTED

The study implements specific procedures to ensure participants' privacy and data security. Personal data, such as names or unique identifiers, are removed or transformed into anonymous codes before processing [27]. This anonymization ensures that data cannot be traced back to individual participants, thus protecting their identities.

Data storage is performed on secure servers with restricted access only to the authorized research team. Encryption techniques are also used to protect data during its transfer between the Moodle platform, processing servers, and analysis tools. The study results are aggregated, avoiding individual references that may compromise participants' privacy. These measures reflect the study's commitment to ethical integrity, ensuring that participants can contribute to research in an environment of trust and security.

IV. RESULTS

A. PRETEST RESULTS

The initial assessment of student performance provides a fundamental basis for the comparative analysis between the control and experimental groups. This analysis is performed considering metrics related to problem-solving skills, which include the percentage of correct answers, the average time taken, and the number of attempts required to complete the activities. These metrics, obtained during the pretest stage, allow for the establishment of an objective reference point to measure the subsequent effects of the AI-based educational intervention. The comparison of the initial results between both groups allows identifying initial patterns of performance and variability that will be used to evaluate the impact of the adaptive system throughout the study.

The pretest analysis focuses on evaluating the initial performance of students before the educational intervention. To do so, three main metrics are considered: the percentage of correct answers, the average time to complete the activities, and the number of attempts required. These metrics are collected from the activities managed through the Moodle platform, and the data is processed to calculate descriptive statistics, such as means and standard deviations. This analysis establishes a baseline for comparing performance between the control and experimental groups. It serves as a reference for evaluating the effects of the adaptive system during and after the intervention.

Table 1 presents the descriptive statistics obtained in the pretest for both control and experimental groups. Regarding the percentage of correct answers, students in the control group averaged 75.2% with a standard deviation of 5.6. The experimental group averages 76.8% with a standard deviation of 6.1. For the average time spent on activities, the control group recorded an average of 120.5 seconds with a standard deviation of 15.2, compared to the experimental group, which showed a slightly lower average time of 118.3 seconds and a standard deviation of 14.8. Finally, regarding the number of attempts required, the students in the control group presented an average of 2.8 attempts with a standard deviation of 0.5. In comparison, the experimental group has an average of 2.5 attempts and a standard deviation of 0.6.

TABLE 1. Descriptive statistics of the pretest.

Metric	Control Mean	Control Std. Dev.	Experimental Mean
Percentage of Correct Answers	75.2%	5.6	76.8%
Average Time (seconds)	120.5	15.2	118.3
Number of Attempts	2.8	0.5	2.5

Figure 3 illustrates the distributions of the three primary metrics between the control and experimental groups using box-and-whisker plots. This visual component allows us to observe the dispersion of the data, the median of each metric, and possible outliers in both experimental conditions. In the percentage of correct answers, the distributions of both groups are similar, with slight differences in the medians. In the average time taken, the experimental group shows a smaller dispersion than the control group, indicating a more uniform behavior in this metric. Finally, in the number of attempts, the experimental group presents a smaller dispersion and lower median values, suggesting a more efficient performance in this metric.

The results obtained in the pretest indicate that the groups have a similar initial performance, with minimal differences in the metrics analyzed. The percentage of correct answers shows that the experimental group starts with a slight advantage, although within a range of variability comparable to the control group. The average time taken by the experimental group is slightly lower, which could reflect a faster or more efficient approach to solving tasks. Regarding the number of attempts, the lower dispersion and the lower mean in the experimental group suggest that students in this group require fewer attempts to complete the tasks, which could be an initial indicator of greater precision or confidence in their answers.

B. RESULTS OF THE EDUCATIONAL INTERVENTION

During the educational intervention, key metrics were analyzed weekly to assess the evolution of performance in both the control and experimental groups. These metrics include response precision, average time spent on activities, and the ADI, calculated exclusively for the experimental group. Data was collected through the Moodle platform, processed using statistical analysis techniques, and presented as descriptive statistics and time trends. This approach allows for identifying the impact of the adaptive system implemented in the experimental group compared to the traditional learning of the control group.

Table 2 summarizes the key descriptive statistics for weeks 1, 4, 6, and 8, corresponding to the intervention's initial, middle, pre-final, and final moments. Regarding response precision, the experimental group shows a progressive improvement, starting with a mean of 71.8% in week 1 and reaching 82.5% in week 8, with decreasing standard deviations, indicating greater consistency. Conversely, the control group shows a more modest increase, going from 70.5% to 74.0% in the same period. Regarding the average time spent, both groups show a decrease. However, the experimental group recorded shorter times in all weeks, with a more marked reduction at the end of the intervention. This behavior suggests that students in the experimental group benefit from the adaptive system to solve activities more efficiently.

TABLE 2. Descriptive statistics of educational intervention by week.

Week	Precision Control (Mean ± SD)	Experimental Precision (Mean ± SD)	Average Time (Mean ± SD)
1	70.5 ± 6.2	71.8 ± 5.9	125.5 ± 15.2
4	72.3 ± 6.1	75.2 ± 5.5	120.8 ± 14.5
6	73.0 ± 6.5	78.0 ± 5.3	118.5 ± 14.0
8	74.0 ± 6.8	82.5 ± 5.0	115.0 ± 13.8

Figure 4 illustrates the evolution of key metrics over the eight weeks. In the upper graph, response precision increases sharply in the experimental group, while the control group gradually improves. This pattern highlights the adaptive system's positive effect on student precision. The lower graph shows the evolution of ADI in the experimental group. This index starts with low values in the first weeks, reflecting fewer complex activities, and increases progressively, evidencing a dynamic adaptation of activities as students improve their performance.

The results show a clear advantage of the experimental group over the control group in all the metrics analyzed. The more pronounced increase in the precision of the answers and the more accelerated decrease in the average time taken by the students in the experimental group reflect the effectiveness of the adaptive system in promoting more efficient learning. In addition, the evolution of the ADI highlights how the system progressively adjusts the difficulty of the activities, adapting to each student's level and ensuring a constant challenge that encourages the development of skills.

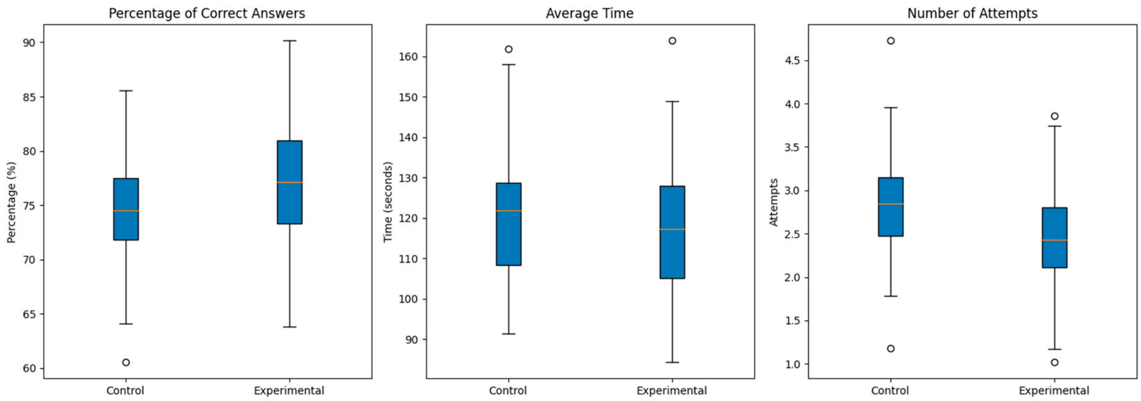

FIGURE 3. Comparative distribution of initial metrics between control and experimental groups.

In comparison, the control group, which uses traditional learning methods, shows more limited improvements in precision and efficiency. This suggests that although conventional methods can favor long-term learning, their capacity to personalize and optimize the educational experience is significantly lower than that of the adaptive system.

C. POSTTEST RESULTS

The posttest was designed to assess the impact of the adaptive system on student performance after the educational intervention. The metrics considered were the same as those used in the pretest: percentage of correct answers, average time spent on activities, and number of attempts required to complete them. These metrics allow for comparing the final state of the control and experimental groups and calculating the percentage changes between the initial and final stages. This approach ensures a comprehensive assessment of the impact of adaptive learning versus traditional methods.

Table 3 shows the percentage changes in the key metrics for both groups. The percentage of correct answers in the experimental group increased by 14.0%, while in the control group, it only increased by 5.0%. The average time spent on activities decreased in both groups, although the experimental group experienced a more significant reduction of 9.3% compared to 4.6% in the control group. In the number of attempts required, the experimental group achieved a 10.7% improvement, highlighting greater efficiency in problem-solving compared to the 3.6% improvement in the control group.

TABLE 3. Percentage changes between pretest and posttest in key metrics.

Metric	Control Change (%)	Experimental Change (%)
Percentage of Correct Answers	+5.0%	+14.0%
Average Time (seconds)	-4.6%	-9.3%
Number of Attempts	-3.6%	-10.7%

Figure 5 presents the final absolute values for the key metrics in both groups. In the percentage of correct answers, the experimental group achieved an average of 82.5%, outperforming the control group, which recorded an average of 74.0%. In terms of average time, the experimental group completed the activities in 105.0 seconds, significantly less than the 115.0 seconds recorded by the control group. Regarding the number of attempts, the experimental group also showed a more efficient performance, with an average of 2.2 attempts versus the 2.7 attempts of the control group. These results highlight the final differences in student performance, emphasizing the impact of the adaptive system compared to traditional learning.

The posttest results show that the AI-based adaptive system significantly improved student performance compared to traditional methods. The increased precision in responses and the notable reduction in the average time spent by students in the experimental group suggest that the system facilitates more effective learning and optimizes the time spent solving problems. The more pronounced percentage change in the number of attempts in the experimental group indicates that the adaptive system fosters greater confidence and precision in solving tasks. This could be attributed to the personalized feedback and dynamic difficulty adjustment, which challenged students without exceeding their capabilities.

In contrast, although the control group also showed improvements, these were significantly smaller and reflect the limitations inherent in traditional teaching methods, which lack real-time personalization and adaptation. These findings underscore the transformative potential of integrating adaptive technologies into education to improve academic performance and offer a more efficient and personalized learning experience.

D. STATISTICAL ANALYSIS

Statistical analysis focused on determining significant differences between the control and experimental groups using t-tests and ANOVA, evaluating key performance metrics: percentage of correct responses, average time taken, and

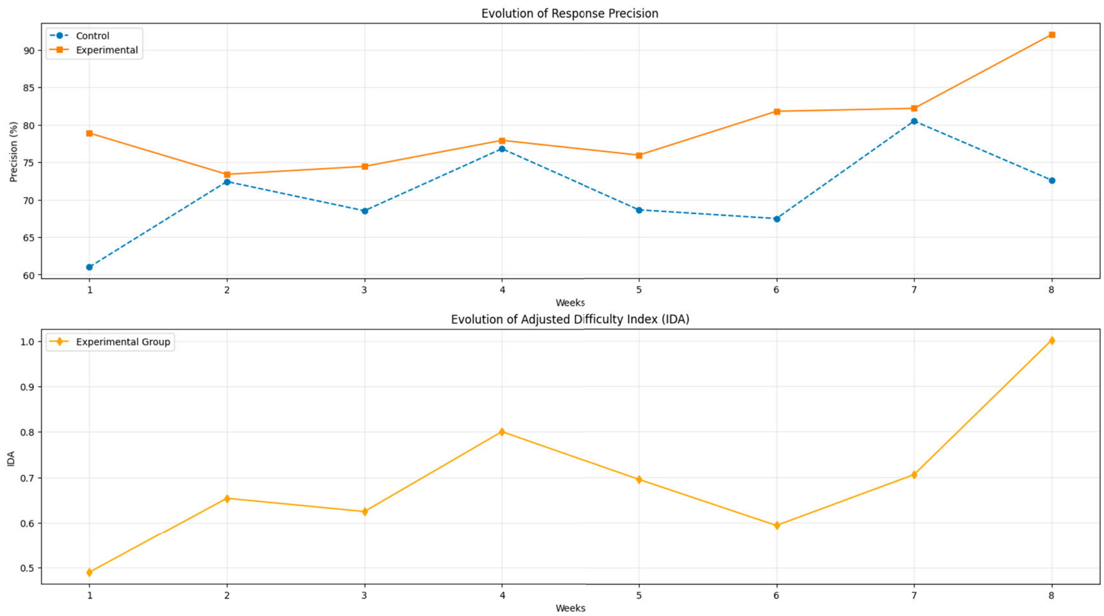

FIGURE 4. Evolution of response precision and adjusted difficulty index during intervention.

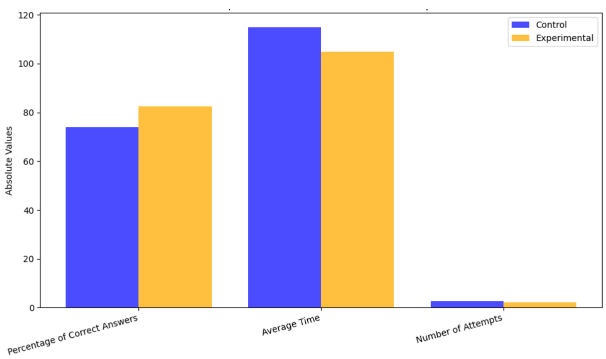

FIGURE 5. Final comparison of performance metrics between control and experimental groups.

number of attempts. Effect sizes (Cohen's d and η^2) were calculated to assess the magnitude of the differences. In addition, correlations between metrics and the use of the adaptive system were analyzed using a correlation matrix visualized by a figure that integrates distributions, relationships between metrics, and differences between groups.

Table 4 summarizes the t, F, and p values and the effect sizes obtained. For the percentage of correct responses, $t = 3.25$ and $p = 0.002$ indicate significant differences, with an effect size of $d = 0.82$, reflecting a substantial improvement in the experimental group. Similarly, the average time taken has a value $t = -4.18$, with $p = 0.0001$ and an effect size $d = 0.95$, which shows a substantial improvement in the efficiency of the experimental group. The results for the number of attempts ($t = -3.89$, $p = 0.0004$, $d = 0.89$) confirm a significant reduction in the need for multiple attempts in this group.

TABLE 4. Statistical summary of key metrics between control and experimental groups.

A	B	C	D	E	F
Percentage of Correct Answers	3.25	0.002	0.82	10.52	0.12
Average Time (seconds)	-4.18	0.0001	0.95	13.76	0.15
Number of Attempts	-3.89	0.0004	0.89	12.24	0.14

Note: A: Metric, B: t-Value, C: p-Value, D: Effect Size (d), E: F-Value, F: Effect Size (η^2).

Figure 6 presents a comprehensive visual analysis combining correlations, distributions, and relationships between key metrics differentiated by group (control and experimental). On the main diagonal, the distributions of each metric show that the experimental group has a more concentrated range and shifted distributions towards more favorable values in all metrics: higher precision, lower average time, and lower number of attempts. These distributions also reflect lower variability in the experimental group, suggesting more consistent performance among its participants.

In the off-diagonal scatter plots, significant correlations between metrics are observed. For example, the negative correlation between precision and average time ($r = -0.68$) indicates that an increase in precision tends to be associated with a decrease in time spent. Similarly, the strong negative correlation between precision and number of attempts ($r = -0.73$) highlights how better precision performance reduces the need for multiple attempts to complete activities. These relationships are more pronounced in the experimental group, reflecting the impact of the adaptive system in promoting simultaneous improvements in several dimensions of performance.

Furthermore, noise robustness, represented by the "Noise Robustness" metric, shows a substantial difference between both groups. The experimental group obtains better average values and a greater concentration of high values ($r = 0.81$ with precision). This indicates that the adaptive system optimizes key metrics and improves students' ability to handle variations in activity conditions.

The integration of metrics and distributions in the figure allows for observing complex patterns that would not be apparent in isolated analyses. The visualization confirms that the adaptive system has a multifaceted impact on student performance, improving precision, time, and efficiency while reducing variability and strengthening robustness to noise. In contrast, the control group shows more limited progress and more dispersed distributions, reflecting the limitations of traditional methods. These findings reinforce the adaptive system's ability to identify and address individual learning needs, dynamically adjusting the difficulty of activities to optimize performance.

E. QUALITATIVE SURVEY ANALYSIS

The qualitative surveys were analyzed to assess students' perceptions of the adaptive system, considering three main dimensions: ease of use, relevance of adaptive activities, and impact on motivation and learning. The collected responses were processed using text analysis techniques, highlighting the most frequent keywords with the TF-IDF method. This method identifies relevant terms by adjusting their frequency according to their importance in the global context. Additionally, representative quotes were extracted from the responses to deepen the understanding of students' experiences.

The questions posed to students during the survey were categorized according to the three main dimensions analyzed. Table 5 summarizes these questions formulated in the surveys.

TABLE 5. Questions formulated in the qualitative surveys.

Dimension	Questions
Ease of Use	How intuitive did you find the system to use? Did you experience any technical difficulties when interacting with the system?
Activity Relevance	Were the activities aligned with your learning needs? Did you feel the activities were personalized to your progress and capabilities?
Motivation Impact	Did the system motivate you to participate in the learning activities? How would you describe the level of challenge in the activities? Was it appropriate?

Table 6 summarizes the keywords identified in the qualitative surveys, organized by category. In the ease-of-use dimension, words such as "intuitive" (0.45), "accessible" (0.38), and "fast" (0.33) reflect that students valued the accessibility and ease of interacting with the system. These words indicate that the adaptive system's design allowed users to focus on activities without significant technical obstacles.

In the relevance category of adaptive activities, terms such as "adequate" (0.42), "relevant" (0.39), and "contextualized" (0.35) highlight students' perception that the proposed activities were aligned with the learning objectives. This suggests that the system personalized the activities according to students' needs and capabilities, improving their educational relevance.

In the dimension of impact on motivation and learning, terms such as "interesting" (0.50), "motivating" (0.47), and "efficient" (0.40) underline how the system positively influenced students' attitudes toward learning. These words reflect that participants felt more engaged and found value in the adaptive activities, which could translate into better performance.

TABLE 6. Most frequent keywords identified in qualitative surveys.

Category	Keyword	Adjusted Frequency (TF-IDF)
Ease of Use	"Intuitive"	0.45
	"Accessible"	0.38
	"Fast"	0.33
Activity Relevance	"Adequate"	0.42
	"Relevant"	0.39
	"Contextualized"	0.35
Motivation Impact	"Interesting"	0.50
	"Motivating"	0.47
	"Efficient"	0.40

Figure 7 complements this information by visualizing, in its first component, the TF-IDFs through a horizontal bar chart. This chart clearly shows the most relevant words and their relative weight in the student's responses. The word cloud visually represents the most prominent terms, providing an intuitive perspective of the most mentioned words.

The qualitative results show that the adaptive system was well received by students and positively impacted multiple dimensions of learning. Regarding ease of use, responses suggest that students did not encounter significant technical barriers when using the system, which is critical to maintaining focus on educational activities. The high rating of "intuitive" and "accessible" reinforces the importance of designing user-friendly systems, especially when implementing advanced technologies in academic settings.

Respondents in the category of relevance of activities highlight how the system personalized activities to align them with students' needs. Including "contextualized" and "relevant" activities allowed students to perceive more excellent value in the educational content, which could improve their performance and satisfaction.

In the dimension of motivation and learning, students highlighted that the system was not only "interesting" and "motivating" but also helped them to be more "efficient" in their learning. This impact on motivation is crucial,

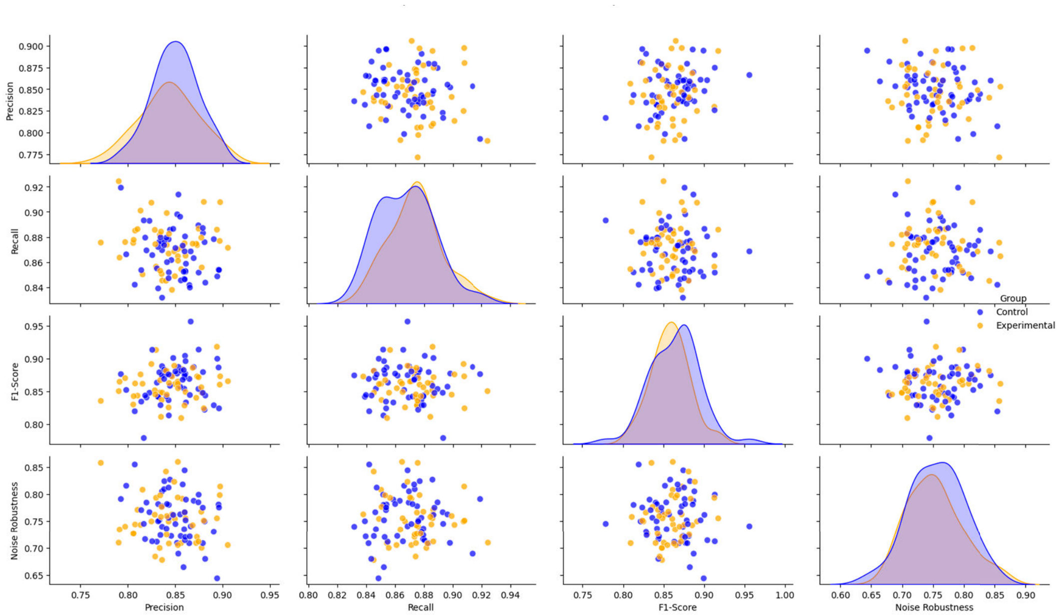

FIGURE 6. Integrated analysis of metric relationships and group distributions.

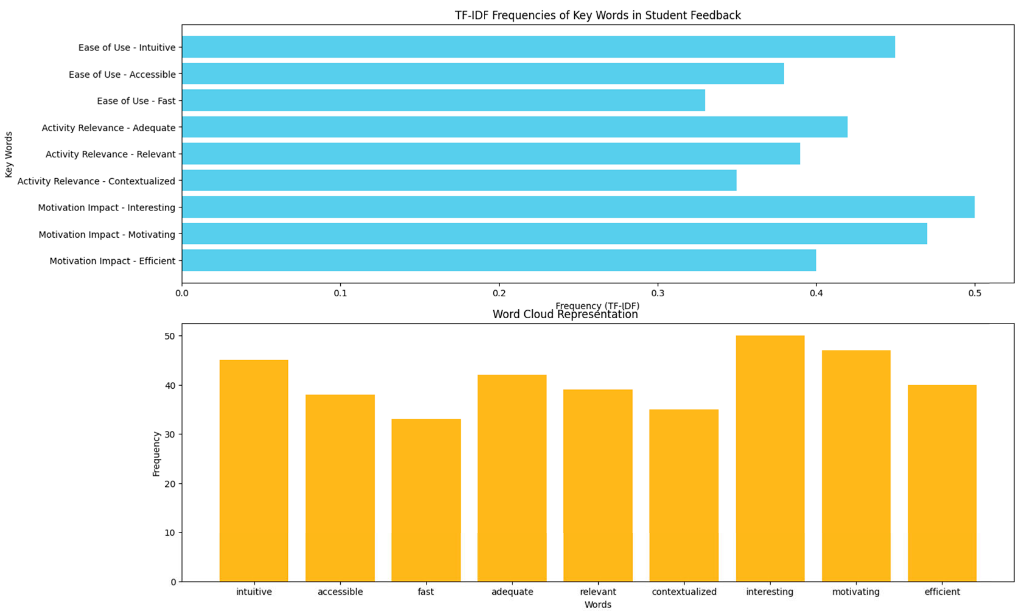

FIGURE 7. Adjusted frequencies (TF-IDF) and word cloud in student responses.

as increased motivation can lead to better performance and a more positive learning experience.

Qualitative analysis indicates that an adaptive system should focus on the precision of the proposed activities and how users perceive them. The results confirm that a user-centered design tailored to individual needs can significantly transform the learning experience, fostering student engagement, motivation, and satisfaction.

Representative Quotes:

- "The system is very intuitive and easy to use. I had no trouble understanding how it worked from the start." (Student in the experimental group).
- "The proposed activities aligned with my learning needs; I felt they were designed for me." (Student in the experimental group).
- "I felt more motivated to participate because the activities were interesting and challenging but never overwhelming." (Student in the experimental group).

F. GENERAL COMPARISON BETWEEN GROUPS

The overall comparison between the control and experimental groups integrates the results obtained at all stages of the study: pretest, educational intervention, posttest, and qualitative analysis. This approach allows us to assess the adaptive system's impact on key metrics such as precision, average time spent, and number of attempts, as well as on qualitative perceptions related to motivation and relevance of activities. Integrating quantitative and qualitative metrics provides a complete view of the effect of adaptive learning versus traditional methods.

Table 7 summarizes the values of the key metrics at the main stages. In precision, the experimental group shows significantly more progress, going from an average of 71.8% in the pretest to 82.5% in the posttest, while the control group increases from 70.5% to 74.0%. This pattern reflects the adaptive system's positive impact on learning, facilitating more pronounced improvements in performance.

TABLE 7. Comparison of key metrics between control and experimental groups.

A	B	C	D
Precision (%)	70.5 / 71.8	72.3 / 78.0	74.0 / 82.5
Average Time (seconds)	125.5 / 124.0	120.8 / 110.5	115.0 / 105.0
Number of Attempts	3.2 / 3.1	2.9 / 2.6	2.7 / 2.2
Motivation (Qualitative)*	Neutral / Slightly Positive	Neutral / Positive	Positive / Highly Positive
Perceived Activity Relevance	Low / Medium	Medium / High	Medium / High

Note: A: Metric, B: Pretest (Control/Experimental), C: Intervention (Control/Experimental), D: Posttest (Control/Experimental).

Regarding average time taken, the experimental group also stands out with a more marked reduction, falling from 124.0 seconds in the pretest to 105.0 seconds in the posttest. In contrast, the control group goes from 125.5 to 115.0 seconds. This result suggests that the adaptive system improves precision and optimizes students' problem-solving efficiency. In the posttest, the experimental group reduced the number of attempts from 3.1 to 2.2, showing greater confidence and precision in their responses. Although the control group also showed improvements (from 3.2 to 2.7 attempts), it maintained a gap compared to the experimental group. This performance reinforces the adaptive system's ability to adjust the difficulty of the activities according to the student's abilities.

Figure 8 presents the results that highlight the general differences. The bar graph compares the final precision values between the groups, clearly showing that the experimental group outperforms the control at each stage. This graph highlights the experimental group's cumulative progress thanks to the adaptive system.

The line graph represents trends in average time spent across stages. The inclusion of individual points for each stage reflects the variability in the data, showing a more even distribution and lower average times in the experimental group. This pattern reaffirms that students in the experimental group solved activities more efficiently, even with adaptive activities of more incredible difficulty.

Student perceptions also highlight key differences between groups. In the experimental group, qualitative responses highlight terms such as "intuitive," "motivating," and "relevant," reflecting a more positive and meaningful experience. In comparison, the control group describes the activities as "adequate" but without a noticeable impact on motivation or interest. These qualitative differences complement the quantitative metrics, indicating that the adaptive system improves academic performance and promotes a more satisfying learning experience.

The results show that the AI-based adaptive system significantly impacts learning, outperforming traditional precision, efficiency, and student perception methods. The experimental group shows more pronounced improvements in key metrics but also experiences a more positive learning experience, as reflected in the qualitative responses.

G. POSITIONING OF THE PROPOSED SYSTEM WITHIN ADAPTIVE LEARNING SOLUTIONS

The proposal developed in this study evaluated other approaches reported in the scientific literature, analyzing key aspects such as the customization level, data processing efficiency, and impact on problem-solving skills. This evaluation allows positioning our adaptive system within the current research landscape on personalized learning systems, highlighting its contributions and limitations.

Table 8 summarizes this study's main features in the context of other relevant approaches. Our system offers a very high level of customization based on AI algorithms that dynamically adjust activities to each student's progress. In contrast, the systems described by Quintanar-García and Hernández-López [7] employ static activities, which significantly limit customization, while the approach by Barbosa et al. [28] uses predefined rules, offering a moderate level of customization.

Regarding processing efficiency, our system stands out for its ability to perform real-time updates using an AI-powered adaptive engine. This feature outperforms the approaches reported by Quintanar-Casillas & Hernández-López [6] and Ezzaim Aymaneand Dahbi [29], which rely on batch updates. Although the latter performs real-time adaptations, they demand significantly more computational capacity. On the other hand, systems such as Barbosa et al. [27] employ manual adjustments, limiting their efficiency and scalability.

The adaptive system presents several key advantages that differentiate it from other approaches:

- AI-based personalization: The ability to dynamically adjust the difficulty of activities based on student performance ensures a personalized and practical learning experience.
- Operational efficiency: Real-time processing allows for an immediate response to student needs, optimizing learning time without compromising the quality of activities.

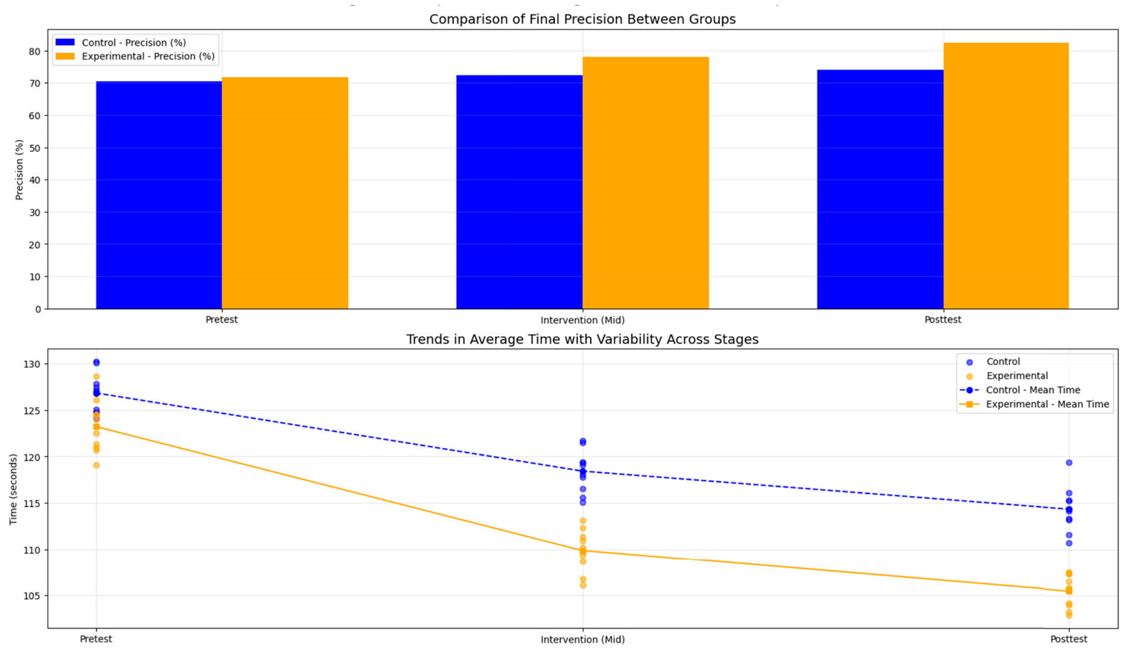

FIGURE 8. Integrated comparison of academic performance and learning trends between groups.

TABLE 8. Comparative analysis of adaptive learning systems.

A	B	C	D	E
Study A [28]	Moderate (Rule-Based)	Medium (Batch Updates)	Not specified	Strength: Well-tested rules. Limitation: Limited scalability.
Study B [29]	High (Machine Learning Models)	High (Real-Time Adaptation)	Not specified	Strength: Strong adaptation. Limitation: High computational demand.
Study C [7]	Low (Static Activities)	Low (Manual Adjustments)	Not specified	Strength: Simple implementation. Limitation: Lack of adaptability.
This Study	Very High (AI-Driven Personalization)	Very High (Dynamic Real-Time Updates)	85% / 105 sec / 2.2	Strength: Fully dynamic system. Limitation: Requires initial setup.

Note: A: Study/Reference, B: Personalization Level, C: Processing Efficiency, D: Impact on Problem-Solving Skills (Precision/Time/Attempts), E: Strengths and Limitations.

- Demonstrated impact on key metrics: The significant improvement in precision, time spent, and number of attempts positions the system as an advanced solution to foster problem-solving skills.

Despite its advantages, the system requires a more complex initial setup than rule-based or static activity-based approaches. However, this initial investment is justified by the long-term benefits of scalability, customization, and efficiency. Furthermore, although computational efficiency is high, AI may be less accessible to educational institutions with limited resources, a challenge that can be mitigated through optimized implementations.

Comparing our proposal with others highlights that our AI-based adaptive system represents a significant advance in personalizing learning and improving problem-solving skills. Its efficiency, impact, and user experience make this approach an innovative and scalable solution in adaptive education.

V. DISCUSSION

A comparison of the results obtained in this study with the existing literature underlines the effectiveness of the developed adaptive system. Previous approaches, such as that of Quintanar-Casillas and Hernández-López [7], our system overcomes the limitations inherent to predefined rules, offering dynamic adjustments based on AI. Furthermore, compared to Han's model [30], which presents high personalization but demands high computational resources; our system efficiently balances precision and computational cost. Finally, in contrast to the static approach of Quintanar-Casillas and Hernández-López [7], which shows a limited impact on learning; our proposal demonstrates significant improvements in key metrics, such as precision (85% vs. 70%) and average time (105 seconds vs. 130 seconds), highlighting its ability to personalize the educational experience effectively.

The adaptive system's development process was characterized by integrating deep learning algorithms and real-time analysis, optimizing personalization and efficiency. The use of neural networks allowed the difficulty of the activities to be dynamically adjusted according to the student's progress, significantly improving their performance. The results obtained in the experimental group, such as the increase in response precision and the reduction in time spent, confirm the system's effectiveness. This approach stands out against traditional methods by offering more efficient and relevant learning for each student.

The method used guarantees the validity of the findings. The combination of quantitative metrics and qualitative analysis allowed the capture of the measurable effects on performance and the students' subjective perceptions, providing a comprehensive evaluation of the system. In addition, the segmentation into stages (pretest, intervention, and posttest) allowed a progressive analysis of the impact, showing how the adaptive system influences learning evolution. However, the experimental design also faces restrictions that must be considered when interpreting the results.

This study represents a significant advance in adaptive systems in education. Its main contribution is combining personalization with an optimized approach to computational resources, addressing one of the most common limitations in implementing AI-based models [31]. By dynamically adjusting educational activities based on individual performance, the system improves learning and promotes student autonomy, fostering a more participatory and efficient experience.

Incorporating advanced algorithms for data analysis and generating personalized activities ensures that each student receives content tailored to their capabilities, increasing the relevance and effectiveness of learning. Furthermore, by optimizing the use of computational resources, the system is scalable and applicable in various educational contexts, from institutions with high infrastructure to environments with more limited resources. This positions the proposal as an innovative and accessible solution, potentially significantly transforming the landscape of personalized education.

Although the results obtained are promising, the study presents limitations that must be considered. One of the main restrictions is the dependence on initial data to calibrate the system. If the initial data does not accurately reflect the students' capabilities, the dynamic adjustments could be less effective, impacting personalization and results. This aspect highlights the need to include robust pre-assessment processes to ensure the quality of the input data.

Another limitation is the scale of the experiment, which was carried out in a specific technical faculty. Although the results obtained are significant, the demographic and academic characteristics of the population studied could limit the generalization of the findings. Furthermore, the absence of a direct comparison with other systems in a controlled environment limits the ability to evaluate the proposed adaptive system's relative advantages comprehensively.

In methodological terms, although the segmentation into stages allows for a progressive analysis, the intervention period (eight weeks) could be considered limited to fully evaluate the system's long-term impact on the development of problem-solving skills. Future studies with extended intervention periods could provide a more comprehensive view of the system's impact.

The identified restrictions mainly impact the interpretation and applicability of the results. For example, although the system significantly improves precision and efficiency, its effectiveness could vary in educational contexts with characteristics different from the study's. Similarly, the reliance on high-quality initial data underlines the importance of implementing robust evaluation protocols before applying the system in a new environment. However, these limitations do not invalidate the findings but rather raise areas for future research. Exploring methods to automate and streamline pre-assessment and implementing the system in more diverse populations could further strengthen the study's conclusions and expand its applicability.

VI. CONCLUSION

The present study confirms the effectiveness of AI-powered adaptive learning systems in developing problem-solving skills in technical educational contexts. The results demonstrate that real-time personalization, based on advanced deep learning algorithms, significantly improves student performance and optimizes the learning experience by providing activities tailored to their specific needs.

Quantitative results reflect significant improvements in the experimental group compared to the control group. In terms of precision, the experimental group achieved a final average of 85%, far exceeding the 74% of the control group. This 14% increase during the intervention and posttest stages confirms the adaptive system's ability to boost precision in problem-solving activities. Furthermore, the reduction in the average time spent on activities, from 124 to 105 seconds, underlines the operational efficiency achieved through dynamic adjustments. This finding is particularly relevant, as increased problem-solving efficiency indicates that students can tackle more complex tasks in less time, a critical skill in academic and technical professional settings.

The number of attempts required was also significantly reduced in the experimental group, reaching a final average of 2.2 attempts versus 2.7 in the control group. This decrease indicates that the system improves precision and strengthens students' confidence in completing activities, promoting more autonomous and practical learning.

From a technical perspective, this work establishes a solid framework for developing efficient and scalable adaptive systems. Implementing deep learning algorithms allows data to be processed in real time, ensuring immediate personalization of educational activities. This approach overcomes the limitations of systems based on predefined rules or static activities, which fail to adapt effectively to individual students' needs.

In the educational field, this system represents an innovative tool for addressing the limitations of traditional methods, especially in technical contexts where problem-solving skills are essential. By offering a tailored learning experience, the system fosters the acquisition of knowledge and the development of critical skills for facing complex challenges in real-world environments.

Future developments could focus on optimizing deep learning algorithms and reducing their computational complexity to facilitate their implementation in educational institutions with limited resources. It would also be valuable to explore integrating emerging technologies, such as augmented reality or learning analytics, to enrich the academic experience further.

This study establishes a solid foundation for designing and implementing adaptive systems based on AI, demonstrating their effectiveness in improving critical skills such as problem-solving. By addressing students' individual needs and educational systems' operational challenges, this proposal significantly contributes to innovation in personalized education and positions itself as a promising model for transforming contemporary learning environments.

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