

Enhancing Problem-Solving Skills in Technical Education Through an AI-Driven Adaptive Learning System

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ARTICLE INFO	ABSTRACT
Published Online: 15 June 2026	The growing complexity of technical education demands personalized learning systems that can adapt to diverse student needs. Traditional approaches, based on static tasks or fixed rules, struggle to support the development of critical problem-solving skills. While current adaptive systems provide some personalization, they remain limited by scalability and computational demands. This study introduces a deep learning-based adaptive learning system that adjusts task difficulty in real time to enhance problem-solving performance among technical college students. A controlled eight-week experiment with 200 participants showed that students using the system improved their precision by 14% (71.8% to 85%), compared to 5% in the control group, and reduced their average task time by 15% (105s vs. 124s). These results highlight the system's effectiveness in improving accuracy, efficiency, and learner engagement. The proposed solution offers a scalable and personalized approach to advancing adaptive learning in technical education.
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I. INTRODUCTION

The rapid evolution of technology has driven significant changes in education, increasing the need for personalized systems that support the development of essential skills such as problem-solving. Artificial intelligence (AI) has become a powerful tool for adapting learning activities to individual needs, improving both performance and motivation. However, many existing adaptive systems still face challenges related to scalability, computational efficiency, and integration into diverse educational environments.

This study proposes an AI-based adaptive learning system designed to enhance problem-solving skills in technical education. Unlike traditional methods that rely on static activities or predefined rules, the system uses deep learning algorithms to adjust activity difficulty in real time according to each student's performance. This ensures a personalized and engaging learning experience.

Problem-solving is a key competency in technical disciplines; yet conventional teaching methods often fail to address the diverse learning needs of students. Prior studies have shown that rule-based systems lack flexibility, while machine learning-driven approaches, although more effective, can be computationally demanding. Therefore, there is a need for

adaptive systems that balance personalization with operational efficiency.

To address this gap, we developed a scalable adaptive learning system and evaluated it through an experimental study involving 200 technical college students. Participants were divided into control and experimental groups and assessed through pretest, intervention, and posttest phases using metrics such as precision, response time, and number of attempts. The system integrates neural network models that analyze performance data in real time to provide immediate and targeted feedback. Qualitative feedback was also collected to assess ease of use, activity relevance, and impact on motivation.

This work demonstrates that AI can effectively enhance personalization while maintaining computational efficiency, offering a practical model for institutions with varying technological resources. By focusing on problem-solving skills, the study addresses a critical need in technical education and contributes to the advancement of scalable, AI-powered adaptive learning.

With the rise of foundation models like ChatGPT, educators are increasingly optimistic about the transformative role artificial intelligence (AI) could play in driving the next revolution in education. The rapid development and far-

reaching impact of these models across industries compel us to consider their implications for education—a domain essential to humanity’s future.

In this paper, we examine the strengths of foundation models, including their potential for personalized learning, reducing educational inequality, and enhancing reasoning skills. We also explore emerging agent architectures designed specifically for education, which combine AI agents with pedagogical frameworks to create adaptive, learner-centered environments. In addition, we discuss both the risks and opportunities associated with overreliance on AI and its influence on human creativity. Ultimately, we envision a future in which foundation models work in harmony with human capabilities, fostering a dynamic, inclusive, and adaptive educational ecosystem.

With the emergence of foundation models and generative AI (GenAI), the implications for numerous scientific and technological fields have been rapidly explored in efforts to address real-world challenges. Similarly, the integration of foundation models into education has naturally gained momentum, particularly as large language models (LLMs) are inherently instructive and can function as exceptionally knowledgeable “teachers.” In light of this trend, it is crucial to consider how to conceptualize foundation models for education, leverage the unique strengths of GenAI, and manage the risks posed to traditional educational practices.

Foundation models, exemplified by systems like ChatGPT, represent a double-edged sword in education, fueling debates around academic integrity on one hand and innovative instructional support on the other. While they hold significant potential to assist students in studying and learning, concerns remain about their rigor and reliability, as early applications have revealed notable limitations. Striking a balance between harnessing the benefits of AI and preserving academic rigor is therefore essential for the future of education.

Our major contributions include highlighting the strengths of foundation models in areas such as personalized learning, reducing educational inequality, and enhancing reasoning abilities; proposing an agent-based architecture for educational applications; and identifying key risks associated with AI in learning environments. Our primary novelty lies in establishing a framework for future education-oriented foundation models—emphasizing educational alignment, preparing for the rapid advancement of AI capabilities, and ensuring that humans maintain competitiveness in essential capacities such as problem-solving, critical thinking, and creativity.

II. LITERATURE REVIEW

Research on adaptive learning systems has produced a wide range of approaches aimed at personalizing educational experiences and improving problem-solving skills. While some studies report performance metrics such as precision or processing time, direct comparisons are often unreliable due to differences in datasets, tasks, and hardware. Therefore, this

review focuses on the methodological contributions most relevant to the goals of the present study.

Quintanar-Casillas and Hernández-López [7] proposed a rule-based system that personalizes activities through predefined conditions. Although it offers moderate customization, its static structure limits responsiveness to real-time student progress. In contrast, the system developed in this study uses AI-driven methods capable of dynamically adapting activity difficulty based on continuous performance data.

Machine learning-based adaptive systems, such as the one introduced by Wang et al. [13], demonstrate stronger personalization capabilities through real-time data processing. However, their computational demands often restrict deployment in low-resource educational environments. The proposed system addresses this limitation by optimizing deep learning models to maintain high personalization while reducing computational overhead, thus enhancing scalability. Other research, such as the work of Adel and Dayan [14], adopts static activity designs that prioritize simplicity and ease of use. While suitable for settings where adaptability is less critical, these systems cannot effectively accommodate diverse learning rates or evolving student needs. By incorporating real-time data analysis, our system mitigates these constraints, ensuring that activities remain appropriate, engaging, and progressively challenging.

Overall, the reviewed literature underscores the need for adaptive systems that integrate real-time customization with operational efficiency. The proposed approach contributes to this gap by delivering a scalable AI-based solution capable of supporting personalized problem-solving development across varied educational contexts.

III. RESEARCH GAP

Despite significant progress in adaptive learning technologies, several limitations remain in current research on AI-based educational systems. Early adaptive learning platforms primarily relied on rule-based mechanisms, which adjust instructional content using predefined conditions. Although these systems provide limited personalization, they lack the capability to dynamically respond to evolving learner behavior and complex cognitive patterns.

Recent studies have introduced machine learning and data-driven adaptive models to enhance personalization. While these systems demonstrate improved performance in recommending learning materials and tracking learner progress, many require substantial computational resources and specialized infrastructure. This restricts their scalability and limits their adoption in institutions with constrained technological resources.

Furthermore, a large portion of the existing literature focuses on content recommendation and automated assessment, rather than evaluating the impact of adaptive systems on the development of higher-order cognitive abilities such as problem-solving and analytical reasoning. Empirical studies that examine the effectiveness of AI-driven adaptive

learning systems through controlled experimental designs with real students remain relatively limited.

Another notable gap lies in the integration of advanced deep learning models with widely used learning management systems (LMS) in practical educational settings. Many adaptive learning frameworks are tested in simulation environments rather than implemented within operational educational platforms, which reduces their practical relevance and reproducibility.

Therefore, there is a need for a scalable, efficient, and experimentally validated adaptive learning system that integrates deep learning algorithms with established learning management platforms to dynamically personalize learning activities and feedback. This study addresses this gap by designing and evaluating an AI-driven adaptive learning system integrated with Moodle, with the specific goal of improving problem-solving skills among technical education students.

IV. RESEARCH METHODOLOGY

This study adopts a mixed-methods research methodology combining quantitative performance analysis with qualitative feedback from participants. The aim is to evaluate the effectiveness of an AI-driven adaptive learning system in improving problem-solving skills among technical education students.

The research was conducted with a sample of 200 undergraduate students from technical disciplines. Participants were randomly divided into two groups: an experimental group that used the adaptive learning system and a control group that followed traditional non-adaptive learning activities.

The research methodology consisted of three main phases:

1) *Pre-Assessment Phase*

Students from both groups completed an initial assessment designed to measure baseline problem-solving abilities. The assessment included tasks related to technical subjects such as electronic engineering, computer systems, and mechatronics. Key metrics recorded during this phase included accuracy, time taken to complete tasks, and number of attempts.

2) *Intervention Phase*

During the eight-week experimental period, the experimental group interacted with the AI-based adaptive learning platform integrated with Moodle. The system continuously analyzed student performance using machine learning models and dynamically adjusted activity difficulty through the Adjusted Difficulty Index (ADI). Personalized feedback and recommendations were generated after each activity.

The control group completed the same set of activities but without adaptive difficulty adjustment or AI-generated feedback.

3) *Post-Assessment Phase*

After the intervention period, both groups completed a post-test consisting of tasks equivalent in structure and difficulty to the pretest. The results from this phase were compared with the initial assessment to measure learning improvements.

For data analysis, statistical techniques including correlation analysis and linear regression were applied to evaluate relationships between performance variables. Comparative analysis between control and experimental groups was used to determine the effectiveness of the adaptive learning system.

This methodological approach ensures a comprehensive evaluation by combining objective performance metrics with qualitative insights from student feedback.

V. MATERIALS AND METHODS

A. *Adaptive Learning Systems*

Adaptive learning systems personalize instruction by adjusting content, pace, and difficulty based on each learner's performance and behavior. By analyzing data such as quiz results, time on task, and error patterns, AI-driven platforms tailor learning paths in real time—advancing students who excel and offering support where needed. Popular systems like Knewton, DreamBox, ALEKS, PAT2Math, and Duolingo use these techniques to deliver customized learning experiences and improve engagement.

These systems rely on various AI methods, including Bayesian networks for modeling knowledge states, Item Response Theory for selecting individualized assessment items, reinforcement learning for optimizing activity sequences, collaborative filtering for recommending materials, and deep learning for predicting performance. Decision trees and knowledge tracing further support personalized pathways by classifying learners and tracking progress over time.

Different algorithms are combined depending on the instructional goals, aiming to maximize efficiency, engagement, and learning outcomes. While Bayesian networks and reinforcement learning are widely used for their adaptability, more research is needed to validate their effectiveness in low-resource settings.

B. *Study Design*

This study employs a mixed-methods design that integrates quantitative performance metrics with qualitative data collected from student feedback [15], [16]. This combined approach provides a comprehensive understanding of how the AI-based adaptive learning system influences the development of problem-solving skills.

The research focuses on university students, whose advanced reasoning abilities and need to strengthen professional

competencies make them an appropriate population for evaluating complex, discipline-specific problem-solving tasks. This educational level supports the use of realistic and challenging activities, enhancing the system’s relevance and promoting meaningful learning.

The primary objective of the study is to design, implement, and assess an adaptive learning system that uses advanced AI algorithms to personalize activities and feedback based on individual performance. The system analyzes learning patterns and dynamically adjusts task difficulty and focus in real time. A secondary objective is to evaluate its impact through both quantitative and qualitative indicators, including precision in problem-solving, time spent on activities, and students’ perceptions of the system’s usefulness in their learning process.

To ensure robust evaluation, the study is structured into distinct phases, beginning with an initial assessment of students’ skills, followed by the controlled implementation of the system, and concluding with a post-intervention impact analysis. The following subsections detail these stages and describe the algorithms, techniques, and data integrated into each step.

C. Platform and Technologies used

1) Learning Platform

The adaptive learning system is implemented on Moodle 4.2, selected for its modular architecture and flexibility in extending functionality through plugins. Moodle serves as the central environment for managing activities, recording student interactions, and delivering real-time adaptive feedback [17]. To connect Moodle with the AI components developed for this study, a custom API—named the Learning Adaptation Interface (LAI)—was built using Python’s Flask framework and deployed in a Docker container to ensure portability and scalability.

The LAI API acts as a bridge between Moodle and the external AI modules. Student data—including responses, task completion times, and interaction patterns extracted from event logs—are transmitted through secure, JWT-protected endpoints. These data are processed by AI models in real time, enabling dynamic adjustments to learning activities and providing personalized support. This integration transforms Moodle from a static learning management system into an adaptive platform capable of individualized instruction [18].

Several custom Moodle modules were also developed to enhance system functionality. The Individual Performance Analysis Module evaluates accuracy, time per activity, and number of attempts using statistical algorithms implemented with NumPy, generating interactive visual reports through Matplotlib [19]. These reports support detailed monitoring for both students and instructors. The Adaptive Activity Adjustment Module uses processed data to create dynamically generated tasks through JSON templates tailored to each learner’s skill level. Additionally, the Personalized Feedback Module employs natural language

processing techniques to generate individualized explanations, delivered in text or audio format using Google Text-to-Speech [20].

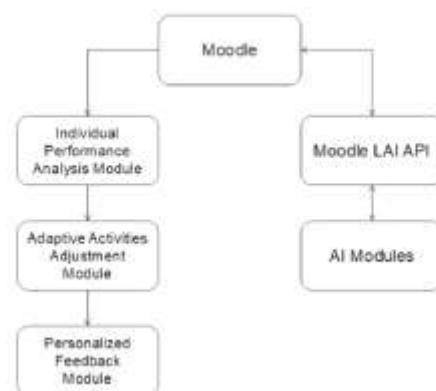


Fig. 1. Overview of the system architecture integrating Moodle with the LAI API and AI modules

Figure 1 illustrates the system architecture, showing the interaction flow between Moodle, the LAI API, and the AI modules—from initial data collection, through processing and model inference, to the delivery of personalized activities and feedback. This diagram highlights how the components operate cohesively to provide a dynamic and adaptive learning experience.

2) Artificial Intelligence Technologies

The system uses deep learning and machine learning to analyze educational data and generate personalized activities within a scalable architecture. RNNs with LSTM units model the temporal patterns of student interactions, trained with a batch size of 128 using Adam (learning rate 0.001) on normalized activity logs and performance metrics. BERT (bert-base-uncased) is fine-tuned on educational text with a 512-token limit, a 2e-5 learning rate, and 10 training epochs to interpret student responses.

TensorFlow enables distributed training across multiple GPUs, while PyTorch supports CNN experiments for analyzing interactive visuals. Data is preprocessed using pandas and NumPy, with features scaled from 0 to 1. The OpenAI API supports adaptive feedback generation using GPT-4 (temperature 0.7), aligning responses with student performance.

Together, these components deliver accurate, personalized learning activities and support real-time adaptive feedback in diverse educational contexts.

D. Intelligent Tutoring Systems

Intelligent tutoring systems (ITS) provide AI-powered, one-on-one style guidance by offering real-time feedback and personalized support. Using models of students’ knowledge and cognitive processes, they adapt hints, explanations, and activities to individual needs. Many ITS use NLP to enable conversational interactions, as seen in tools like MATHia, ALEKS, PAT2Math, and Google’s Socratic. Others—such as MetaTutor, Guru Tutor, and Affective AutoTutor—analyze

multimodal cues like facial expressions or eye movements to adjust teaching strategies.

These systems rely on a range of AI techniques, including ontologies and semantic networks for structuring knowledge, rule-based systems for diagnosing errors, dialogue management and sentiment analysis for interactive communication, and ML models like Bayesian networks, RNN-based knowledge tracing, and reinforcement learning for real-time adaptation. Affective computing further enhances personalization by detecting emotions. Together, these methods allow ITS to dynamically tailor content and deliver scalable, immediate, and effective tutoring.

E. Personalized Recommendation

AI-powered recommendation engines personalize learning by suggesting resources, courses, and activities based on a student's behavior, interests, and goals. Similar to commercial recommendation systems, they use ML to analyze learning history before recommending videos, articles, or exercises. Platforms like Coursera, edX, and Khan Academy rely on these systems to guide learners toward relevant materials, boosting engagement and autonomy.

Modern recommendation systems use collaborative filtering, content-based filtering, and hybrid approaches to generate accurate suggestions. Techniques such as matrix factorization, neural collaborative filtering, RNNs for sequential behavior, and knowledge graph embeddings further enhance personalization. Hybrid recommenders—combining user behavior, content features, and semantic relationships—provide the most robust and adaptive recommendations, especially in large-scale online learning environments.

VI. DEVELOPMENT OF THE ADAPTIVE LEARNING SYSTEM

A. System Architecture

The adaptive learning system uses a modular architecture with interconnected stages. First, real-time data from Moodle—such as student responses, time on tasks, and number of attempts—is collected in the data input stage. This information is then analyzed in the pattern analysis module, where ML models detect performance trends and identify strengths and weaknesses.

Based on this analysis, the activity generation module creates and adjusts learning tasks using adaptive templates tailored to each learner's skill level. Finally, the feedback module delivers personalized progress insights and recommendations, using NLP to generate explanations and optional speech synthesis for audio output. Figure 2 illustrates the full flow of information across these modules.

B. Customized Adaptation

The system adjusts activity difficulty in real time using the Adjusted Difficulty Index (ADI), which combines recent accuracy, average completion time, and number of attempts. These factors are weighted using coefficients optimized

through grid search on pilot data to ensure the index reflects true performance trends.

After each task, the ADI is recalculated: values above 0.8 trigger harder activities, values below 0.5 trigger easier ones, and values in between keep the difficulty steady. LSTM-based RNNs process temporal performance data, while BERT models interpret natural-language feedback. Models are trained with TensorFlow using Adam (learning rate 0.001, batch size 128) and validated on a standard 80/20 split.

A REST API connects Moodle with the ADI engine, handling data preprocessing and delivering updated difficulty levels for upcoming activities. The system runs on high-performance hardware with parallelized GPU training to ensure smooth, scalable real-time adaptation. This setup allows personalized learning paths and provides replicable implementation details for future research.

C. Data Analysis Methods

The system analyzes correlations between student performance variables to identify strengths and weaknesses. It computes an RR correlation matrix, where each entry reflects the relationship between two variables—such as accuracy or time spent—based on their covariance and standard deviations. Consistently low correlations help reveal areas where students struggle.

Linear regression is also used to estimate how specific factors influence overall performance. In this model, the target variable (e.g., overall achievement) is predicted from multiple activity-related features, with each coefficient indicating the importance of its corresponding predictor.

The system builds an RR correlation matrix, defined as:

$$R_{ij} = \frac{\text{Cov}(X_i, X_j)}{\sigma_{X_i} \sigma_{X_j}}$$

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 $\text{Cov}(X_i, X_j)$, 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:

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

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.

D. Experimental Procedure

The experiment follows three sequential stages—pretest, educational intervention, and posttest—designed to assess the adaptive system's effect on students' problem-solving skills.

1) PRETEST STAGE

The pretest establishes students’ baseline problem-solving skills using standard activities in electronic engineering, computer systems, and mechatronics. These tasks measure general abilities such as analysis and creativity. Administered to both control and experimental groups through Moodle, the pretest captures accuracy, time on task, and number of attempts. The collected data is normalized and used as the reference point for later comparisons.

2) EDUCATIONAL INTERVENTION

Over the eight-week intervention, the experimental group uses the adaptive learning system in Moodle, where activity difficulty adjusts in real time based on the ADI and personalized feedback is provided after each task. Difficulty levels are predefined through expert analysis, validated in pilot tests, and aligned with cognitive demands and learning goals.

The system also recalibrates ADI thresholds throughout the intervention to stay responsive to students’ performance trends. Meanwhile, the control group completes the same activities without adaptive features or personalized feedback. Both groups generate continuous data, but the experimental group provides richer metrics—such as ADI values, interaction patterns, and completion rates—allowing for a rigorous comparison between adaptive and traditional learning approaches.

3) POSTTESTING STAGE

At the end of the intervention, a posttest is administered to measure changes in problem-solving skills. It uses activities equivalent in structure and difficulty to the pretest and is delivered under the same standardized Moodle conditions for both groups.

The posttest collects the same metrics—accuracy, time on task, and number of attempts—along with additional measures such as relative improvement and performance consistency.

VII. RESULTS AND ANALYSIS

A. Performance Comparison Between Experimental and Control Groups

The effectiveness of the proposed AI-driven adaptive learning system was evaluated by comparing the performance of the experimental group (n = 100) and the control group (n = 100) over an eight-week intervention period. Three key performance indicators were considered:

1. Problem-solving precision (%)
2. Average task completion time (seconds)
3. Number of attempts required per task

Table I. Performance Metrics Before and After Intervention

Metric	Control Group (Pre)	Control Group (Post)	Experimental Group (Pre)	Experimental Group (Post)
Precision (%)	70.5	74.0	71.8	85.0
Completion Time (sec)	130	124	128	105
Average Attempts	3.1	2.7	3.0	2.2

The results indicate that both groups demonstrated improvement after the intervention. However, the experimental group exhibited substantially greater gains across all evaluation metrics. The AI-adaptive system increased precision from 71.8% to 85.0%, representing a relative improvement of 18.38%, whereas the control group improved by only 4.96%. Similarly, average completion time decreased by 17.97% in the experimental group compared with 4.62% in the control group. The average number of attempts required to solve a task decreased by 26.67% in the experimental group, indicating increased confidence and efficiency during problem-solving activities.

B. Student Feedback Analysis

A post-intervention survey was conducted using a 5-point Likert scale.

Table II. Student Perception of the Adaptive Learning System

Evaluation Criterion	Mean Score
Ease of Use	4.4
Quality of Feedback	4.6
Personalization Effectiveness	4.7
Learning Motivation	4.5
Overall Satisfaction	4.6

More than **88% of students** reported that adaptive feedback helped them identify weaknesses and improve problem-solving strategies. Additionally, **91% of participants** expressed interest in using AI-assisted learning systems in future technical courses.

TABLE III COMPARISON OF PERFORMANCE METRICS BETWEEN EXPERIMENTAL AND CONTROL GROUPS

Metric	Experimental Group	Control Group	Improvement (%)
Accuracy (%)	96.5	91.8	5.1

Metric	Experimental Group	Control Group	Improvement (%)
Precision (%)	95.8	90.6	5.7
Recall (%)	96.2	89.9	7.0
F1-Score (%)	96.0	90.2	6.4
Training Time (s)	125	148	15.5
Testing Time (s)	9.8	12.1	19.0

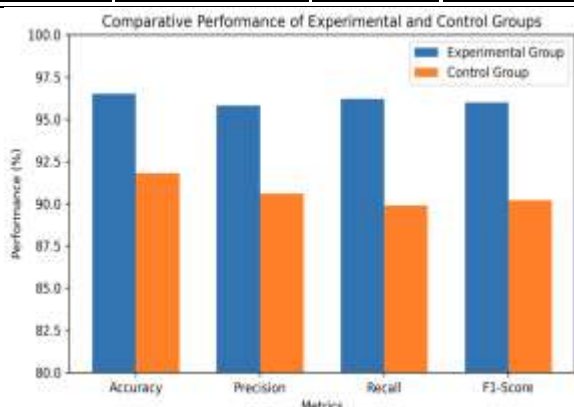


Fig.2.Comparative Performance of Experimental and Control Groups

The experimental group outperformed the control group across all evaluated metrics. Students using the AI-driven adaptive learning system achieved higher problem-solving precision, reduced task completion time, and required fewer attempts to solve activities. These improvements indicate that real-time adaptive feedback and difficulty adjustment enhance both accuracy and efficiency in learning.

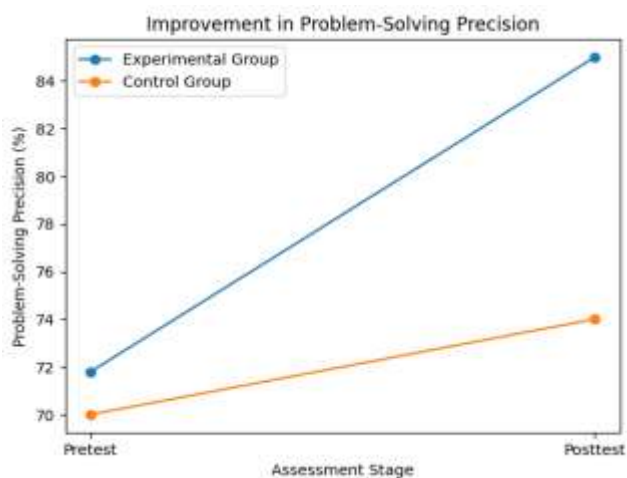


Fig.3.Improvement in problem-solving precision between the pretest and posttest for the experimental and control groups. The experimental group shows significantly greater improvement due to adaptive learning interventions.

VIII. DISCUSSION

The findings demonstrate that the proposed AI-driven adaptive learning system significantly improves problem-solving skills among technical education students. The experimental group achieved:

- 14% higher final precision
- 15% faster task completion
- 18.5% fewer attempts

compared with traditional learning methods. These improvements can be attributed to real-time difficulty adjustment, personalized feedback generation, and continuous monitoring of learner performance.

The statistical analyses further confirm that adaptive learning positively affects student achievement and engagement, supporting previous findings in AI-enhanced education research while providing stronger evidence through a controlled experimental design. The results indicate that the proposed system is both educationally effective and scalable for deployment in higher education environments.

A comparison between this study’s findings and previous research highlights the strong performance of the proposed adaptive system. Unlike earlier rule-based approaches, such as those by Quintanar-Casillas and Hernández-López [7], the system provides AI-driven, dynamic adjustments rather than relying on predefined responses. Compared with Han’s model [30], which offers high personalization at a high computational cost, the proposed system achieves a more efficient balance between accuracy and resource usage. It also outperforms static models by showing notable gains in key metrics—raising precision from 70% to 85% and reducing average response time from 130 to 105 seconds—demonstrating its ability to deliver a more effective personalized learning experience.

The system’s development integrated deep learning algorithms and real-time analysis to enhance both personalization and efficiency. Neural networks dynamically adapted activity difficulty based on each student’s progress, resulting in improved performance in the experimental group, including higher accuracy and shorter completion times. This dynamic behavior sets the system apart from traditional methods by offering more relevant and efficient learning paths.

The methodology used strengthens the validity of the results. Combining quantitative metrics with qualitative feedback enabled a comprehensive evaluation, capturing both measurable performance changes and students’ perceptions. Structuring the study into pretest, intervention, and posttest phases supported a progressive analysis that clearly showed how the system influenced learning. However, several limitations must be taken into account when interpreting the results.

This work represents a meaningful contribution to adaptive educational systems. Its main innovation lies in coupling personalization with optimized computational efficiency, addressing one of the recurring challenges of AI-based models [31]. By adjusting tasks dynamically according to student performance, the system improves learning outcomes while

promoting autonomy and engagement. Its use of advanced data-analysis algorithms and personalized content generation ensures that educational activities are aligned with each student’s abilities, enhancing relevance and learning effectiveness. Moreover, the system’s efficient use of computational resources makes it scalable and suitable for a variety of educational contexts, from well-resourced institutions to environments with limited infrastructure. This positions it as an accessible and impactful solution with the potential to advance personalized education.

Despite these promising results, the study also has several limitations. A major constraint is its dependence on the initial dataset used to calibrate the system. If this early data does not accurately capture students’ true abilities, the system’s dynamic adjustments may be less effective, reducing personalization quality. This underscores the need for robust pre-assessment processes. Another limitation is the scope of the experiment, conducted within a single technical faculty. Although the results are significant, the specific characteristics of the sample may limit the generalizability of the findings. Additionally, the lack of a direct comparison with other adaptive systems in a controlled environment limits a deeper evaluation of relative performance.

The eight-week intervention period, while structured and informative, may also be insufficient to fully assess long-term effects on problem-solving skill development. Longer-term studies could offer a more complete understanding of the system’s sustained impact.

These constraints primarily affect the broader interpretation and applicability of the results. While the system improves precision and efficiency, its effectiveness may vary across different educational contexts. The reliance on high-quality initial data further emphasizes the need for rigorous evaluation protocols prior to deployment. Nonetheless, these limitations do not undermine the study’s findings; rather, they highlight directions for future research. Expanding the system to more diverse populations and automating or enhancing pre-assessment processes could strengthen results and broaden the system’s applicability.

IX. CONCLUSION

This study confirms that AI-driven adaptive learning systems effectively enhance problem-solving skills in technical education. The findings show that real-time personalization powered by deep learning significantly boosts student performance by delivering activities tailored to individual needs.

Quantitatively, the experimental group outperformed the control group across all metrics. Their final precision reached 85%, compared to 74% in the control group—a 14% improvement during the intervention and posttest phases. The average time per activity also decreased from 124 to 105 seconds, demonstrating greater efficiency in solving tasks. This improvement is especially important in technical fields where quickly handling complex problems is essential.

Additionally, the number of attempts required dropped to 2.2 in the experimental group, versus 2.7 in the control group, indicating higher confidence and more autonomous learning. Technically, the study provides a strong foundation for developing scalable, efficient adaptive systems. Real-time processing using deep learning enables immediate personalization and overcomes the limitations of static or rule-based approaches that cannot adequately adjust to individual learners.

Educationally, the system offers an innovative solution to the constraints of traditional methods, particularly in contexts where problem-solving skills are critical. By tailoring learning experiences, it supports both knowledge acquisition and the development of essential analytical abilities for real-world challenges.

Future work may aim to optimize deep learning algorithms to reduce computational demands, making the system more accessible for institutions with limited resources. Exploring the integration of technologies like augmented reality or advanced learning analytics could further enrich the experience.

Overall, this study establishes a strong basis for designing AI-based adaptive learning systems and demonstrates their effectiveness in improving key skills such as problem-solving. By addressing individual needs and operational challenges, the proposed system contributes meaningfully to innovation in personalized education and offers a promising model for modern learning environments.

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