ASM Sc. J., 19, 2024
https://doi.org/10.32802/asmscj.2023.1895

Transforming Rural and Underserved Schools with AI-Powered Education Solutions

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This study explores the application of artificial intelligence (AI) technology in promoting inclusive learning in underserved schools. By integrating personalised learning platforms, intelligent tutoring systems, and automated management tools, this research evaluates the impact of AI on academic performance, learning engagement, and teacher workload. The experimental results show that AI-driven personalised learning paths and real-time feedback mechanisms significantly improved student learning outcomes, particularly in subjects such as mathematics and science. In addition, teachers' administrative burdens were effectively reduced through automated tools. The study also analyses challenges such as insufficient infrastructure and data privacy protection, proposing targeted technical solutions. This paper provides practical guidance for policymakers and educational institutions to promote the implementation of AI technology in low-resource environments.

Keywords: Inclusive learning; artificial intelligence; underserved schools; personalised learning; intelligent tutoring systems; automated management

I. INTRODUCTION

Educational equity is one of the core issues in global social development. However, many underserved schools still face challenges such as a lack of resources and low teaching quality (Zhang, 2024a). These schools are often located in economically underdeveloped or remote areas, lacking sufficient educational resources, infrastructure, and qualified teachers, which prevents students from receiving the same quality of education as those in more developed regions. To bridge this gap, the application of artificial intelligence (AI) technology in education has increasingly attracted attention.

AI technology, through personalised learning platforms, intelligent tutoring systems, and automated management tools, can provide tailored learning paths based on students' learning progress and needs, while also reducing teachers' administrative workloads and improving teaching efficiency (Luo, 2024). However, most current research focuses on AI applications in resource-rich schools, with limited studies on how AI can be applied in resource-constrained underserved schools. Thus, finding effective ways to introduce and promote AI technology in environments with inadequate infrastructure has become a critical issue to address.

The goal of this research is to explore how AI technology can be integrated to achieve inclusive learning in underserved schools. Specifically, this paper will evaluate how personalised learning platforms use data-driven real-time analysis to optimise learning paths and improve students' academic performance; analyse how intelligent tutoring systems, through personalised feedback mechanisms, enhance students' learning engagement and self-directed learning abilities. This research will explore how automated management tools reduce teachers' administrative workloads and improve overall teaching efficiency.

By addressing challenges such as insufficient infrastructure, data privacy protection, and teacher technical capability in underserved schools, this study offers a feasible AI solution framework for policymakers and educational

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institutions, supporting the global promotion of AI in education.

II. LITERATURE REVIEW

In recent years (Bearman, Ryan & Ajjawi, 2023), artificial intelligence (AI) has gradually become an important innovative tool in the field of education, especially in the applications of personalised learning, intelligent tutoring systems, and automated management tools. AI technology, through big data analysis, machine learning algorithms, and automated tools, can provide personalised learning paths for students and offer real-time teaching feedback and support for teachers, thereby optimising the teaching process and improving learning outcomes (Abdallah & Greco, 2021).

For example, Zawacki-Richter *et al.* (2021), through a systematic review of AI applications in higher education, found that personalised learning platforms can dynamically adjust learning content and progress based on students' real-time performance, significantly enhancing academic performance (Zawacki-Richter *et al.*, 2021). These systems not only offer targeted recommendations based on students' learning needs but also effectively reduce the burden on teachers in lesson planning and classroom management, improving teaching efficiency.

Although AI technology has been widely applied in education in developed regions, research on its application in underserved schools remains relatively scarce. These schools often face challenges such as weak infrastructure and limited teacher technical capacity, making traditional AI technology difficult to implement in such environments (Cao *et al.*, 2020). Therefore, exploring lightweight AI technologies adapted to the needs of resource-constrained schools has become a critical issue that needs to be addressed.

A. Technical Needs and Challenges in Underserved Schools

Underserved schools are usually located in economically underdeveloped or remote areas and lack essential educational resources, modern infrastructure, and sufficient qualified teachers (Ali & Abdel-Haq, 2021). The student population in these schools often comes from disadvantaged backgrounds, including ethnic minorities, low-income families, or immigrant communities. Unequal educational opportunities result in poor academic performance and low learning engagement among these students.

The main challenges of introducing AI technology in these schools include insufficient infrastructure, unstable network connectivity, limited hardware availability, and a lack of technical support for teachers and administrators. For example, Santos and Boticario (2021) mentioned that students with disabilities in underserved schools often face difficulties in adapting to new technologies, further limiting the application of AI in education (Santos & Boticario, 2021).

Additionally, teachers and administrators' ability to adapt to new technologies is often weak, and the lack of adequate training support is another barrier to the promotion of AI technology. Teachers need to handle many administrative tasks when introducing AI systems, and limited time and energy make it difficult for them to effectively use these tools (Celik *et al.*, 2022). Furthermore, student data privacy protection is a growing concern, and achieving effective data analysis while ensuring privacy has become a significant challenge.

B. Existing Research Solutions

To address these challenges, researchers have proposed a series of technical solutions aimed at adapting AI technology to low-resource environments. First, lightweight AI models can reduce the demand for computing resources, enabling AI systems to operate in environments with limited hardware availability. For example, Benaich and Hogarth (2021) mentioned that edge computing technology can reduce dependence on cloud computing resources by processing data locally, which is particularly important in environments with unstable networks (Benaich & Hogarth, 2021).

Moreover, differential privacy technology offers new solutions for protecting student data privacy. Differential privacy ensures that even if individual student data changes, the overall dataset's output remains stable, thereby protecting personal privacy while allowing AI systems to conduct effective data analysis. Abdallah and Greco (2021) demonstrated the practical application of differential privacy in AI systems and explored the potential of implementing these technologies in educational data (Abdallah & Greco, 2021).

In terms of teacher training, researchers have proposed online teacher support systems and continuous training programs to help teachers gradually adapt to AI technology (Zhang, 2024a). This approach not only reduces the cost of teacher training but also provides timely technical support during actual teaching, enhancing teaching efficiency.

C. *Innovations of This Study*

Although existing research has provided various technical solutions to address the challenges of applying AI technology in underserved schools, many unresolved issues remain. The innovation of this study lies in proposing a closed-loop learning ecosystem that integrates personalised learning, intelligent tutoring systems, and automated management tools, specifically designed for resource-constrained schools. By combining lightweight AI models, differential privacy technology, and edge computing, the system can operate efficiently in low-bandwidth and limited hardware environments (Wei *et al.*, 2020).

Additionally, this study proposes a modular automated management tool that can be gradually introduced into school administration, helping schools optimise resource allocation and improve teaching efficiency. Through data-driven real-time feedback mechanisms, the system can continuously optimise students' learning paths, assisting teachers in better monitoring and guiding student learning processes (Salas-Pilco, Xiao & Hu, 2022).

D. *Future Research Directions*

Future research should further explore the applicability of AI technology in different cultural contexts and educational systems, particularly in the global promotion of AI technology, addressing issues such as cultural differences, technological adaptability, and costs (Li, 2024a; Zhang, 2024a). Moreover, as AI technology continues to evolve, emerging technologies such as affective computing and deep learning provide new possibilities for personalised learning. Future research could delve deeper into the application of these technologies in inclusive learning (Leong, 2024b).

III. MATERIALS AND METHOD

A. *Research Framework and Model*

This study proposes an inclusive learning system framework that aims to provide targeted educational support for underserved schools using artificial intelligence technology. The core modules of the framework include a personalised learning platform, an intelligent tutoring system, and automated management tools. By integrating lightweight AI models, edge computing (Cao *et al.*, 2020), and differential privacy technologies (Abdallah & Greco, 2021), the system can operate in low-resource environments while continuously optimising students' learning paths and teaching efficiency through a closed-loop feedback mechanism.

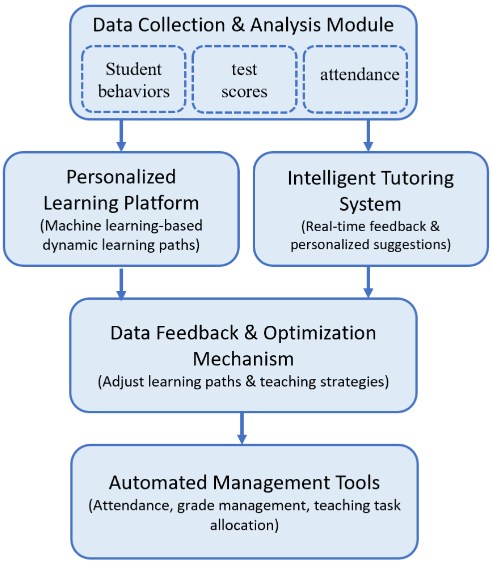

Figure 1. Research Framework: AI-based Inclusive Learning System for Underserved Schools

Underserved schools face several major challenges, including insufficient infrastructure, a lack of educational resources, and excessive teacher workload. This study addresses these challenges by designing an AI technology framework adapted to low-resource environments. The three core modules of the framework (personalised learning platform, intelligent tutoring system, and automated management tools) support each other to form a closed-loop feedback learning ecosystem. The system is designed to operate efficiently in low bandwidth and low computing resource environments and can continuously optimise learning and teaching outcomes through data feedback.

1. Personalised learning platform

The goal of the personalised learning platform is to provide personalised learning paths for each student through machine learning algorithms, helping them learn according to their progress and needs. To adapt to the specific environment of underserved schools, the platform utilises a lightweight AI model, reducing its dependency on computing resources and the network, allowing it to operate even in low bandwidth or offline environments (Chen, Chen & Lin, 2020). The optimisation process of the personalised learning platform is based on machine learning, with the core goal of improving the model's predictive accuracy by minimising the loss function:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell\left(f(x_i;\theta), y_i\right) \tag{1}$$

Where $L(\theta)$ is the loss function, measuring the difference between the model's predictions and actual results.

$f(x_i;\theta)$ represents the model's prediction for sample x_i, and y_i is the actual result.

ℓ is the specific form of the loss function (e.g., mean squared error or cross-entropy).

To reduce the consumption of computing resources, the personalised learning platform adopts model pruning and quantisation techniques to reduce the model size, ensuring efficient operation in resource-limited environments.

2. Intelligent tutoring system

The intelligent tutoring system aims to provide real-time feedback to students through deep learning technology and simulate teachers' teaching behaviour to assist students in self-directed learning. Based on the collected learning data, the system generates learning recommendations and processes data locally using edge computing to reduce dependence on cloud computing, enabling the system to function even in environments with unstable network connectivity (Leong, Leong & San Leong, 2024b). The neural network in the intelligent tutoring system predicts through forward propagation with the following mathematical expression:

$$z^{[l]} = W^{[l]}a^{[l-1]} + b^{[l]} \qquad a^{[l]} = \sigma(z^{[l]}) \tag{2}$$

$z^{[l]}$ is the linear combination of neurons in the lll-th layer, $W^{[l]}$is the weight matrix, $a^{[l-1]}$ is the activation output of the previous layer, and $b^{[l]}$ is the bias term.

The activation function $\sigma(z^{[l]})$ converts the linear combination result into a non-linear output, determining the input for the next layer.

The intelligent tutoring system also improves computational efficiency through adaptive learning rate adjustment and model compression, ensuring high accuracy and efficiency in resource-constrained environments.

2. Automated Management Tools

The automated management tools are designed to reduce the administrative burden on teachers and optimise school management processes. These tools use data automation and optimisation algorithms to assist schools in tasks such as attendance tracking, course scheduling, and grade management (Chiu *et al.*, 2023). The automated management tools are based on a linear programming model to optimise resource allocation in educational management, expressed as:

$$Maximise \sum_{i=1}^{n} c_i x_i \quad Subject\ to \sum_{i=1}^{n} a_{ij} x_i \leq b_j, j = 1,2,\cdots,m \tag{3}$$

Where c_i is the coefficient of the objective function, representing the benefits or priorities of resources, and x_i is the decision variable (such as course time allocation). The constraints a_{ij} and b_j define the resource limitations (such as teacher working hours or classroom capacity).

To adapt to the needs of different schools, the automated management tools adopt a modular design. Schools can gradually introduce functional modules as needed, ranging from simple attendance management to complex course scheduling and resource optimisation, helping schools progressively achieve automated and data-driven management (Chu *et al.*, 2022).

4. Data feedback and closed-loop optimisation mechanism

The key to the framework lies in continuously optimising learning and management processes through a data feedback mechanism. The system continuously adjusts learning paths and teaching strategies through real-time analysis of student, teacher, and management data, forming a closed-loop feedback system (Leong, 2023). To protect student privacy, the system incorporates differential privacy technology, mathematically expressed as:

$$\mathbb{P}[M(D) = O] \leq e^{\epsilon} \cdot \mathbb{P}[M(D') = O] \quad (4)$$

Where M is the data processing algorithm, D and D' are neighbouring datasets, O is the algorithm's output, and ϵ is the privacy protection parameter. Differential privacy ensures that even if a student's data is modified, the system's output will not change significantly, thus protecting student privacy.

B. Data Collection and Preprocessing

1. Data sources

The data used in this study primarily comes from the following sources:

Student learning data: This includes homework completion, test scores, and engagement levels, sourced from the school's Learning Management System (LMS). The data was collected using standardised tools to ensure consistency and completeness. These data reflect students' learning processes and outcomes, providing the foundation for generating personalised learning paths.

Attendance data: This records student attendance and is sourced from the school's attendance system. The data is collected through an automated attendance system to reduce human error, ensuring accuracy and reliability. This data is used to analyse student engagement and assess the system's impact on student behaviour.

Teacher feedback data: Collected through teacher input, this data records teaching progress and student performance. Standardised questionnaires and teacher evaluation forms were used to ensure objectivity and consistency. This data provides the intelligent tutoring system with teachers' observations and assessments, helping to improve the personalised learning experience for students.

2. Data preprocessing

Before feeding the data into the model, the following data preprocessing steps were performed:

Data cleaning: Missing and anomalous data were removed to ensure data quality. Interpolation and mean imputation were used to handle missing values, ensuring data completeness. Additionally, outlier detection methods were applied to remove significant outliers and reduce noise that could affect model performance.

Normalisation: Features such as learning scores and engagement levels were normalised to ensure consistency across data. This helped eliminate scale differences between features, improving the model's training performance. Min-Max normalisation was employed, scaling feature values to a range between [0, 1], ensuring that all features carry equal importance during model training.

Data augmentation: To enhance data representativeness, synthetic data was generated for missing entries. For example, using a nearest-neighbour approach, reasonable missing data points were generated to ensure balanced data distribution. Additionally, minority class data was augmented to balance the dataset's class distribution, improving the model's generalisation ability.

C. Experimental Design and Procedure

1. Experimental setup

A control group and an experimental group design were employed to evaluate the impact of the AI-driven personalised learning platform and intelligent tutoring system on students' academic performance and learning engagement. The experiment lasted 12 weeks and involved 200 students aged 12 to 15 from three underserved public schools in remote areas. Each group, the experimental and control group, consisted of 100 students, with balanced gender ratios, baseline scores, and age distributions to ensure fairness.

Experimental group: Students used the personalised learning platform and intelligent tutoring system. The system adjusted each student's learning path in real-time based on their learning behaviour data and provided personalised feedback. Students were required to use the system for at least 30 minutes each day. The platform logged students' online learning time, learning activities, and feedback responses. Data was automatically collected by the LMS, ensuring completeness and accuracy.

Control group: Students continued with traditional teaching methods, and teachers followed a standard curriculum. No personalised learning support was provided to the control group. Learning data was collected through teacher assessments and standardised testing tools.

The experiment controlled for other variables that could influence students' learning outcomes, such as teaching styles and classroom environments. All teachers participating in the experiment received standardised teaching training to ensure consistency in teaching styles. Additionally, school management ensured that the students in both the experimental and control groups were balanced in terms of gender, age, and baseline scores, minimising the influence of confounding factors.

2. Evaluation metrics

The experiment used the following three key metrics to evaluate the effectiveness of the AI system:

Academic performance: Standardised tests were used to compare the performance of students in the experimental and control groups across different subjects. The test questions were reviewed by educational experts to ensure validity and reliability across subject areas. The tests were administered at the beginning and end of the experiment to precisely measure students' academic progress.

Learning engagement: LMS logs were analysed to evaluate the learning behaviour of students in both groups, including online learning time, discussion participation frequency, and timely submission of assignments. Particular attention was paid to student attendance, classroom interaction, and participation in extracurricular learning activities to comprehensively assess the AI system's impact on learning engagement.

Teacher workload: Teacher workload was assessed through teacher surveys. The surveys were designed using a Likert five-point scale to evaluate changes in teacher preparation time and administrative tasks (such as attendance tracking and assignment grading). The surveys were administered before and after the experiment, and statistical analysis was used to determine changes in workload.

D. Data Analysis Methods

1. Analytical Tools

This study used Python's Scikit-learn and Pandas for data cleaning, feature engineering, and model training. Additionally, TensorFlow was used for constructing and training deep learning models, and SPSS was used for statistical analysis to ensure the significance and reliability of the data analysis results. These tools were selected for the following reasons:

Scikit-learn: A powerful machine learning library, particularly suitable for classification, regression, clustering, and model validation. This study used it for model evaluation, cross-validation, and comparing different models' predictive performance, such as Random Forest and Support Vector Machine (SVM), to optimise the personalised learning platform's recommendation system.

Pandas: Provides efficient data manipulation capabilities, ideal for cleaning, feature extraction, and transformation of large-scale educational data. Pandas enabled efficient processing of students' learning behaviour data, ensuring the accuracy of the analysis.

TensorFlow: A highly efficient deep learning framework used for building complex neural network models. In this study, Convolutional Neural Networks (CNNs) were employed to analyse students' learning behaviour data and predict the optimal learning path.

SPSS: In terms of statistical analysis, SPSS allows for effective significance testing, hypothesis validation, and variance analysis. SPSS was used in this study for significance testing, ensuring that the differences in academic performance between the experimental and control groups were statistically significant.

2. Statistical analysis methods

The following statistical methods were primarily used in this study:

Independent sample t-test: Used to compare the performance differences between the experimental and control groups, evaluating the impact of the personalised learning platform on students' academic performance (Chu *et al.*, 2022). The hypothesis assumed that the experimental group students' performance would be significantly higher than that of the control group, with the significance level set at 0.05. Through the t-test, we verified the effectiveness of the personalised learning system in improving academic performance.

Analysis of variance (ANOVA): Used to compare the differences in student engagement under different learning modes, analysing the changes in online learning time, discussion participation frequency, and other metrics between the experimental and control groups (Leong, 2024a). This study used one-way ANOVA to explore the effectiveness of the personalised learning platform and intelligent tutoring system in improving learning engagement.

Regression analysis: Used to analyse the correlation between system usage time and learning outcomes, particularly the relationship between daily system usage time and academic performance improvement (Leong, 2022). Through a multiple linear regression model, we evaluated how learning behaviours (e.g., online time, participation frequency) impacted students' performance.

Independent variables: System usage time, engagement (attendance, discussion frequency).

Dependent variable: Students’ academic performance improvement (as measured by the improvement in final exam scores).

Control variables: Student gender, age, and baseline scores, to ensure objectivity in the results.

Through regression analysis, we can explore the comprehensive impact of system usage time on learning performance and provide insights for future system optimisation. The following technical challenges were encountered during the research:

Incomplete data: Due to missing records for some students, data augmentation techniques and interpolation methods were used to handle these missing data points. For example, missing score data was filled using a nearest-neighbour interpolation method to ensure that the generated data resembled actual data. Emphasising data completeness ensured that the data used to train the model was of high quality, improving model reliability.

Unstable network connectivity: In underserved schools, network connectivity was unstable. By introducing edge computing, most computational tasks were completed on local devices, reducing dependency on cloud computing and allowing the system to function effectively even in offline environments. This was achieved by deploying lightweight models on student devices to ensure basic learning support when the network was interrupted.

Limited resources: To address limited hardware resources, the system used model pruning and quantisation techniques to reduce the computational complexity of the neural network model, ensuring efficient operation on low-power devices. Pruning reduced the number of neurons, while quantisation simplified floating-point calculations to lower-precision calculations, thus reducing both computation and storage demands. These optimisation measures ensured the system maintained good performance in resource-constrained environments (Holmes, Tuomi & Pereira, 2022).

IV. RESULT AND DISCUSSION

This study evaluates the impact of the AI-driven learning system on academic performance, learning engagement, and teacher workload through experiments conducted in underserved schools. The experimental results clearly demonstrate the positive effects of the personalised learning platform, intelligent tutoring system, and automated management tools in optimising teaching quality, improving student performance, and reducing teacher workload. Below is a detailed analysis of the results.

The students in the experimental group showed a significant improvement in academic performance across all subjects, particularly in subjects such as mathematics and science, which require logical thinking and reasoning skills. The specific data are shown in Table 1.

Table 1. Comparison of Academic Performance Improvement

Subject	Performance Improvement in Control Group (%)	Performance Improvement in Experimental Group (%)
Mathematics	6%	23%
Science	4%	18%
Language	5%	20%
Arts	3%	19%

As shown in Table 1, the improvement in the experimental group was greatest in mathematics and science, with increases of 23% and 18%, respectively. This suggests that personalised learning paths, which dynamically adjust learning content by analysing students' real-time data, help students better understand problems and improve their problem-solving abilities. The improvements in language and arts were also significant, indicating that the AI system not only excels in STEM subjects but also fosters progress in communication skills and creative thinking.

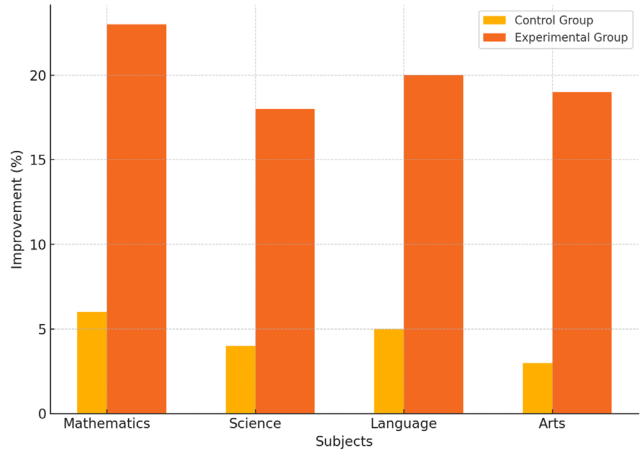

Figure 2. Comparison of Academic Performance Improvement

The experimental data also show that using personalised learning paths significantly reduced the time students spent learning, particularly during repeated practice and knowledge consolidation. By automatically analysing students' errors and weaknesses, the AI system can recommend the most appropriate learning materials, improving the effectiveness and efficiency of learning.

The students in the experimental group showed a significant increase in learning engagement, especially in terms of online learning time and participation in classroom discussions. The real-time feedback provided by the intelligent tutoring system allowed students to engage more actively in the learning process. The specific data are shown in Table 2.

Table 2. Comparison of Learning Engagement

Indicator	Growth in Control Group (%)	Growth in Experimental Group (%)
Increase in Online Learning Time	35%	125%
Increase in Participation in Classroom Discussions	20%	80%

The online learning time for the experimental group increased by 125%, compared to only 35% for the control group. Additionally, the experimental group saw an 80% increase in participation in classroom discussions, compared to 20% in the control group. This result shows that the AI system, by providing personalised learning paths and real-time feedback, stimulates students' interest in learning and their intrinsic motivation to study.

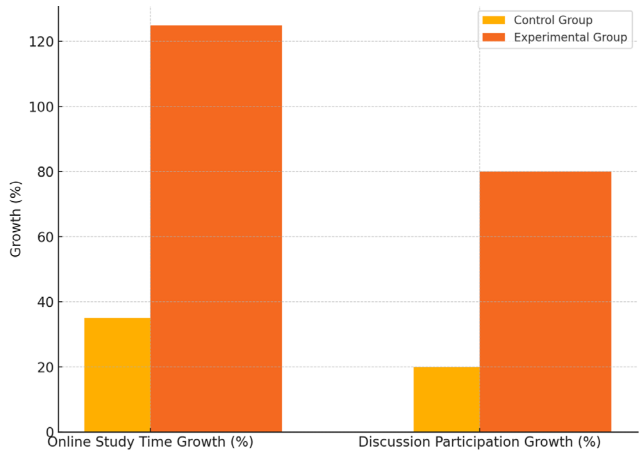

Figure 3. Comparison of Learning Engagement Growth

By automatically collecting and analysing student behaviour data, the AI system can make real-time adjustments and provide feedback on students' learning behaviours, helping them master knowledge more quickly while enhancing interaction and the frequency of feedback during the learning process. This instant and personalised feedback mechanism effectively promotes the development of students' study habits.

The workload of teachers in the experimental group was significantly reduced, particularly in terms of lesson preparation and administrative tasks. With the help of automated management tools, teachers were able to spend more time and energy on teaching innovation and student guidance. The specific data are shown in Table 3.

Table 3. Comparison of Reduction in Teacher Workload

Indicator	Reduction in Control Group (%)	Reduction in Experimental Group (%)
Reduction in Lesson Preparation Time	10%	40%
Reduction in Administrative Tasks	15%	30%

Teachers in the experimental group reduced their lesson preparation time by 40%, and administrative tasks were reduced by 30%, far exceeding the 10% and 15% reductions in the control group. This indicates that the automated management tools effectively reduced teachers' workload, allowing them to focus more on personalised teaching and course design.

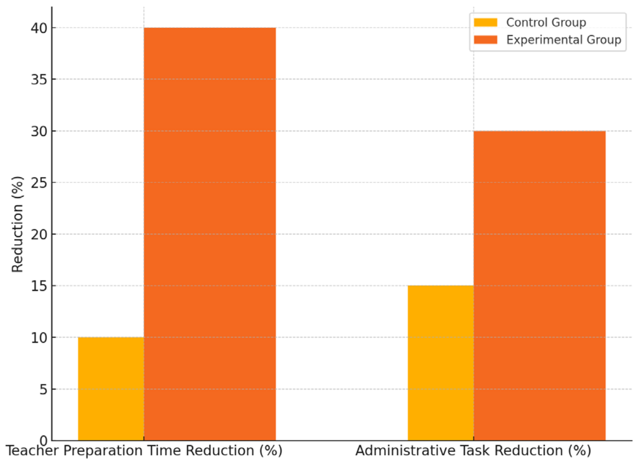

Figure 4. Comparison of Reduction in Teacher Workload

The AI system not only helps students optimise their learning paths but also simplifies teachers' daily tasks through automated processes such as attendance tracking, grade management, and course scheduling. This feature not only improves school management efficiency but also enhances the quality of teaching.

Through an in-depth analysis of the experimental data, this study verifies the effectiveness of the AI-driven learning system in underserved schools, particularly in improving academic performance, enhancing learning engagement, and reducing teacher workload. These results further support the potential of AI technology in promoting educational equity, optimising resource allocation, and enabling personalised learning.

The AI system, by analysing students' learning data in real time, can adjust the learning content according to each student's progress, interests, and weaknesses (Leong, 2024d). The significant improvement in mathematics and science performance among students in the experimental group indicates that AI-powered personalised learning paths not only help students address knowledge gaps but also improve learning efficiency, especially in subjects requiring complex reasoning and logical thinking.

Real-time feedback and personalized recommendations significantly boosted students' learning motivation. The students in the experimental group exhibited substantially higher online learning time and classroom participation compared to the control group. This demonstrates that the AI system's feedback mechanism can help correct student errors in a timely manner and provide encouragement, fostering good study habits and improving long-term learning outcomes.

With the help of automated management tools, teachers' administrative tasks and preparation time were greatly reduced, allowing them to devote more time and energy to personalised teaching and innovative course design. This feature is particularly suitable for resource-constrained schools, effectively alleviating teacher stress and improving teaching outcomes.

This study verifies that AI-driven learning systems can be equally effective in resource-limited schools. AI technology not only enables personalised learning for students but also provides automated management tools for teachers and schools, promoting the optimal allocation of educational resources. In situations where educational resources are unevenly distributed, AI technology can help achieve educational equity by providing students in different regions with the same high-quality learning opportunities.

By integrating personalised learning, intelligent tutoring, and automated management tools, this study offers an innovative solution for teaching in underserved schools (Li, 2024b; Zhang, 2024d). Future research can further explore how more innovative algorithms, such as affective computing and deep learning, can optimise students' personalised learning paths or how these technologies can be adapted and promoted across different cultural contexts to ensure the applicability and widespread adoption of AI technology in education globally.

Although this study demonstrates the effectiveness of AI technology in improving academic performance and optimising educational resources, some limitations remain. First, the sample size of this study is relatively limited, and future research should consider validating these results in a broader educational context. Additionally, the long-term stability of the AI system and students' long-term learning outcomes require further research. Future research can explore how AI technology can be more effectively integrated into teachers' teaching styles and how to address ethical issues related to AI, such as data privacy and fairness.

V. CONCLUSION

This study empirically validated the effectiveness of AI-driven personalised learning systems, intelligent tutoring systems, and automated management tools in underserved schools. The application of these systems not only improved academic performance and enhanced learning engagement but also reduced teacher workload, thereby advancing educational equity.

The major innovation of this study lies in introducing AI technology into resource-constrained environments, specifically in underserved schools, and validating that personalised learning paths and automated teaching management tools can significantly improve teaching quality even with limited resources (Bearman, Ryan & Ajjawi, 2023). This finding breaks through the existing literature, which predominantly focuses on resource-rich environments, and broadens the application scenarios of AI in education. Additionally, the closed-loop feedback mechanism adopted in this study, which optimises learning paths through data-driven real-time adjustments, significantly enhances students' learning outcomes. This provides new directions for the widespread application of AI technology in the future.

The experimental results showed that the AI system, through real-time analysis of students' learning data, helps students adjust their learning paths according to their needs, significantly improving academic performance, especially in subjects such as mathematics and science that require logical thinking. This process, enabled by the dynamic adjustment of personalised learning paths and real-time feedback, provides precise learning support for students at different levels. At the same time, the AI-driven automated management tools effectively reduce teachers' repetitive tasks, allowing them to devote more energy to personalised teaching.

The real-time feedback mechanism of the AI system significantly enhanced students' learning engagement and motivation. The significant increase in online learning time and participation in discussions among students in the experimental group validates this. Personalised feedback not only improved students' learning experience but also fostered their ability to engage in self-directed learning, playing an essential role in forming long-term study habits (Zhang, 2024c).

The application of AI technology provides a new solution for underserved schools, helping these schools achieve optimised allocation of educational resources. Through personalised learning paths and automated management tools, students can receive high-quality learning experiences even in resource-limited environments, and teachers can more efficiently manage their teaching tasks (Celik *et al.*, 2022). This finding contributes to promoting educational equity on a global scale, enabling the widespread application of educational technology across different economic and cultural backgrounds.

Despite the significant potential of AI technology in education, its application still faces some technical challenges. First, ensuring data privacy and security while maintaining the system's personalisation and feedback accuracy is a critical issue that needs to be addressed. Second, the long-term effects of AI systems and their impact on students' continued learning require further research. Moreover, how to integrate AI technology with the practical needs of different cultural and educational backgrounds to address global educational disparities is another area worthy of future exploration (Crompton & Burke, 2023).

Future research could further explore the adaptability of AI technology in various types of schools, especially in regions with diverse cultural backgrounds and infrastructure disparities, to validate its potential for broader dissemination. Additionally, research could explore how to reduce the cost of implementing AI technology to make it more feasible on a global scale. As AI technology rapidly evolves, future studies should also examine how to incorporate emerging technologies such as affective computing and deep learning into teaching to provide students with more personalised and emotionally supportive learning experiences (González-Calatayud, Prendes-Espinosa & Roig-Vila, 2021).

By combining personalised learning systems, intelligent tutoring systems, and automated management tools, this study offers an effective solution to address issues of inadequate educational resources and low teaching efficiency. These findings not only validate the effectiveness of AI technology in improving student learning outcomes, enhancing engagement, and reducing teacher workload but also provide a solid theoretical foundation and empirical support for the future application of AI technology globally. Future research should continue to explore how AI technology can further promote educational equity, ensuring that every student has access to fair and high-quality learning opportunities.

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