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Construction of English Wisdom Classroom Based on Educational Big Data Mining

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The aim of this study is to explore the academic outcomes resulting from the implementation of an intelligent classroom based on educational big data mining in English teaching. Ninety-eight students at HS middle school were randomly divided into two groups: experimental and control. The experimental group were exposed to wisdom classroom teaching, while traditional teaching methods were used for the control group. The results showed that the experimental group performed significantly better than the control group in terms of English scores, online learning time, assignment submission frequency, class interaction frequency, and course satisfaction. Students in the experimental group showed higher learning motivation and self-efficacy. Moreover, the evaluation of technology use in the smart classroom also received positive feedback, indicating low frequency technical failure and high user-interface friendliness. These findings validate the effectiveness of the smart classroom in improving students' learning outcomes, enhancing attitude to learning, and optimizing teaching-student interaction. The study results highlight the application potential of big data technology in the field of education and provides important a scientific basis and practical guidance for future education models.

Keywords: English wisdom classroom; Big data mining; Teaching application; Controlled experiment

1. INTRODUCTION

With the rapid development of globalization and information technology, the traditional education model has been unable to meet the needs of modern learners. By mining big data, traditional quantitative research methods can be optimized [1]. In the field of language learning, traditional classroom teaching methods tend to be ineffective and inefficient, and students often lack motivation to learn because there is limited interaction within the classroom and programs are not individualized. The increasing use of big data in the education sector offers new possibilities for language teaching. By mining and analyzing large-scale education data, students' learning habits, progress, and difficulties can be deeply understood, leading to the establishment of a more appropriate and efficient smart classroom. Smart classroom can use advanced data analysis tools to achieve the dynamic adjustment of teaching content and teaching methods, so as to improve teaching quality and students' learning effectiveness. Therefore, the construction of a smart classroom based on educational big data mining not only combines technology and education: it is also key to improving language learning outcomes.

Nowadays, research on the smart classroom based on educational big data mining is growing rapidly, exploring many aspects of innovation and application. These studies not only focus on the optimization of teaching methods, but also investigate ways to strengthen teacher-student interaction, and use technology for the analysis of students' emotions and attitudes.

Luo et al. (2022) demonstrated how speech recognition technology is used to improve teaching interaction in a smart classroom based on advanced information technology [2]. The work of Tian et al. (2022) [3] and Zhu et al. (2023) [4] focused on real-time analysis of student emotion by using Mini-XCeption architecture and NAGNet framework, aiming

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Table 1 Exclusion and inclusion criteria.

Criterion Type	Criterion Description
Inclusion	1. Registered high school students.
	2. Ages between 14 and 18 years old.
	3. Parents and students agree to sign the informed consent form.
Exclusion	1. Long-term record of absenteeism.
	2. Special needs or disabilities in English learning.
	3. Currently participating in other research or experiments.

to optimize the teaching process by identifying students' emotional states to adjust teaching strategies accordingly.

In terms of teaching strategies, Huang and Wang (2021) discussed music wisdom teaching strategies in the context of "Internet +", highlighting the importance of technology integration in improving learning experience [5]. Gao et al. (2021) showed the potential of cloud classroom mode based on data mining and processing as a means of improving educational efficiency through optimization analysis of online intelligent teaching mode [6].

Regarding the practical application of smart classroom, Wang and Guo (2019) analyzed the state of classroom teaching based on goal detection model and pointed out the possibility of optimizing classroom management by conducting data analysis [7]. Zhang (2020) discussed the wisdom teaching practice based on the Rain Classroom from the perspective of college English teaching, demonstrating its effectiveness in improving teaching interaction and learning motivation [8]. In the broader field of educational technology application, Yuan et al. (2023) explored the practical application of virtual reality (VR) intelligent teaching model in Open University English courses in China, revealing the potential of the educational meta-universe in enhancing immersive learning experience [9].

The construction of a smart classroom involves the development and application of technology, and also needs to consider the human factors in the educational environment, such as teacher training and student acceptance. At the same time, with the continuous advancement and application of smart classroom technologies, there is an increasing need for policies and regulations to ensure the effective and ethical use of these technologies. Through the accumulation and development of these studies, the smart classroom based on educational big data mining is gradually becoming an important force to promote educational innovation and improvement.

It is of great theoretical and practical significance to explore the construction of an English wisdom classroom based on educational big data mining. This study can enrich and deepen the theoretical system of wisdom education and provide scientific basis for the teaching strategy and teaching mode that characterize a wisdom classroom. By analyzing the outcomes achieved by applying big data in English teaching, data-driven teaching methods can be evaluated and optimized, and new theoretical support can be provided for the field of educational technology. By means of experiments to verify the actual impact of a smart classroom based on big data mining on improving students' English learning effectiveness, this study can provide specific implementation plans and improvement measures for schools and educational institutions. This not only improves students' learning efficiency and interest, but also helps teachers to better understand students' needs and adjust teaching content and methods accordingly. With the comprehensive development of education informatization, the research will also provide decision support for education policy makers and promote the popularization and application of smart education technology.

2. DATA AND METHODS

2.1 General Information

Ninety-eight students from HS Middle School were selected as the research subjects, and randomly assigned to two groups, each comprising 49 students. One group (experimental) was exposed to English wisdom classroom teaching based on educational big data mining; the other group (control) were taught using traditional methods.

Prior to conducting the experiment, and in order to ensure its fairness and rigor, both groups were tested to determine their level of English competency in listening, reading, writing and speaking. Statistical methods verified that there was no significant difference in the overall scores of the two groups before the experiment, which ensured the consistency of the baseline data between the two groups at the beginning of the experiment. This process was very important to ensure the validity of subsequent experimental results used to determine the specific impact of the smart classroom teaching mode on students' achievement in English language learning.

During the experiment, for the smart classroom model, big data technology was used to collect and analyze students' learning behaviors and achievements in real time, so that teachers could adjust teaching strategies and course contents according to the gathered data. Students in the control group continued to follow the school's standard lesson plan without teachers using any big data-enabled instruction tools. The purpose of this design was to explore the differences between the big data-driven teaching mode and the traditional teaching methods, and determine the approach that resulted in the most improved English-learning outcomes.

2.2 Exclusion and Inclusion Criteria

When conducting the English wisdom classroom research based on educational big data mining, it is crucial to ensure that the selected research objects have the appropriate conditions and control the variables that may affect the research results. Therefore, clear exclusion and inclusion criteria were established to ensure the accuracy and reliability of the study data.

As shown in Table 1, the inclusion criteria are designed to ensure that students enrolled in the study have the basic learning conditions and are eligible to participate in the research. Age and registration information ensures a representative and consistent student body. At the same time, obtaining the consent of parents and students ensures ethical compliance. The exclusion criteria are designed to eliminate variables that may affect the results of the study due to special circumstances, such as long-term absence from school that may affect learning outcomes, special needs or disabilities that may require specific teaching methods, and participation in other studies that may interfere with the results of the study. These criteria ensured the reliability and generalizability of the research results.

2.3 Experimental Methods

2.3.1 Experimental group

The intelligent classroom teaching method based on educational big data mining can greatly improve the adaptability and interactivity of teaching by offering a highly personalized learning experience and real-time feedback mechanism. By analyzing students' behavioral data, teachers can more precisely identify students' learning needs and difficulties, thereby providing targeted guidance and resources. This approach not only enhances students' motivation to learn, but also increases learning efficiency, as the content and pace of instruction can be adjusted in real time to suit the actual performance of students. The intelligent classroom was implemented as follows:

(1) The education big data platform was integrated with the learning management system (LMS) to collect the learning behavior data of students, including learning time, participation in activities, timely submission of homework, etc.

(2) Data analysis tools were applied to mine the collected data so as to identify students' learning habits and level of proficiency, and a personalized learning path was recommended.

(3) Each student was provided with customized learning resources and exercises such as video explanations, interactive simulations, and augmented reality (AR) content through an intelligent recommendation system.

(4) By means of the real-time feedback mechanism, teachers could adjust the teaching plan and teaching strategy according to the student learning data provided by the system to improve the teaching and learning outcomes.

2.3.2 Control Group

Students in the control group continued to learn according to the school's standard curriculum plan without the use of any big data-supported teaching tools. The teaching methods applied were:

(1) The traditional classroom teaching mode was adopted. Teachers led the course process and students learnt by listening to lectures, taking notes and participating in class discussions.

(2) Standard textbooks and teaching plans were used, and the course content and progress milestones were pre-set and not adjusted according to students' individual learning needs.

(3) Generally, classroom interaction was restricted to teachers' questions and students'answers, and was not supported by data or analysis.

(4) Assessment methods comprised traditional written tests and oral expressions, focusing mainly on assessing students' memory and comprehension skills.

2.4 Indicators and Criteria

2.4.1 Observing Indicators

In the research on the English wisdom classroom based on educational big data mining, the selection of observation indicators is crucial. These should include both the assessment of traditional teaching outcomes and multi-dimensional learning analysis driven by big data technology. Effective observation indicators can reveal in depth the impact of smart classroom teaching on students' learning effectiveness, and indicate the practical application value of educational big data mining in teaching practice.

As shown in Table 2, the indicators for each dimension are designed to comprehensively evaluate the impact of a smart classroom in terms of teaching and learning, and the actual effect of technology application. The academic achievement index directly indicates the student's learning achievement and is the core of evaluating the teaching effect. By recording students' daily learning activities, learning behavior indicators provide quantitative data on the learning process and help to clarify the relationship between learning behavior and learning outcomes. The learning attitude dimension focuses on students' psychological response and emotional attitude. These soft indicators are particularly important for evaluating the humanized design of learning environment and its psychological impact on students. The dimension related to the effect of technology use assesses the practical application of educational technology, and these indicators help determine the effectiveness of technological solutions and their sustainability in educational practice. Through the comprehensive observation of these multidimensional indicators, the research can comprehensively evaluate the effect and potential of the smart classroom model based on the mining of educational big data.

2.4.2 Judgment Criteria

In this study, criteria were applied to determine whether the differences in performance between the experimental and control groups in terms of different observational measures were statistically significant. These criteria are designed to ensure the rigor and science of the research results, so that the research conclusions are valid. All quantitative data (such as academic achievement, online study time, frequency of assignment submission, etc.) were analyzed for differences between the two groups using an independent sample T-test.

Table 2 Observation indicators.

Dimension	Indicator Abbreviation	Observation Indicator
Academic Performance	A1	Pre-experiment grades
	A2	Post-experiment grades
	A3	Regular performance grades
	A4	English listening test scores
	A5	English speaking test scores
Learning Behavior	B1	Study time
	B2	Frequency of homework submission
	B3	Number of classroom interactions
	B4	Frequency of seeking teaching resources
	B5	Level of engagement
Attitude towards Learning	C1	Self-efficacy
	C2	Learning motivation
	C3	Satisfaction with the course
	C4	Acceptance of teaching methods
	C5	Assessment of learning pressure
Technical Use Effectiveness (Experimental Group)	D1	Platform usage frequency
	D2	Evaluation of effectiveness of data mining tools
	D3	Personalized learning path
	D4	Frequency of technical failures
	D5	Evaluation of user interface friendliness

For qualitative data (e.g., learning motivation, satisfaction with the course, etc.), Chi-square tests were used to obtain the difference in distribution between the two groups.

SPSS software was used for data processing and analysis. The significance level was set at 0.05; that is, when the P-value was less than 0.05, the difference between the two groups was considered statistically significant. Descriptive statistical analysis was performed with 95% confidence interval to provide the mean and standard deviation of each observation index.

For complex multi-dimensional data or continuous tracking data, multivariate analysis methods such as ANOVA or linear regression models may be used to further explore the relationship between multiple factors that influence learning effectiveness.

2.5 Statistical Analysis

SPSS was used for statistical analysis, and the number of use cases and percentage of relevant indicators of students in the two groups were expressed. For the χ^2 test, the learning status of students in the two groups after the experiment was expressed by $x \pm s$, and for T-test, $P < 0.05$ was statistically significant.

(1) Descriptive statistical analysis

The mean and standard deviation were calculated to indicate the student's learning outcomes. Equations (1) and (2) are shown below.

$$\text{mean} = \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$\text{Standard deviation} = s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i \bar{x})^2} \tag{2}$$

(2) χ^2 test

This was conducted to determine whether there were significant differences in the distribution of qualitative variables (such as learning attitudes and satisfaction) between the two groups of students. The χ^2 test is shown in the following Equation (3).

$$\chi^2 = \sum \frac{(O-E)^2}{E} \tag{3}$$

where O represents the observed frequency and E represents the expected frequency.

(3) Independent sample t test

This was applied to determine whether there was a statistically significant difference between the mean values of two groups of students on quantitative variables such as test scores. The T-test is shown in Equation (4).

$$t = \frac{\bar{x}_1 \bar{x}_2}{s_P\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \tag{4}$$

where S_P is the combined standard deviation, the calculation formula is shown in Equation (5):

$$s_p = \sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}} \tag{5}$$

where n_1, n_2 are the sample sizes of the two groups respectively, and, S_1, S_2 are the standard deviations of the two groups.

(4) Significance level

A significance level ($P < 0.05$) was set, meaning that when the P-value obtained by the test was less than 0.05, the difference between the two groups was considered statistically significant.

Table 3 Descriptive statistical analysis.

Dimension	Indicator	Experimental Group Data (x ± s)	Control Group Data (x ± s)	χ^2	t-value	p-value
Basic Information	Age	15.6 ± 1.2	15.5 ± 1.1	-	0.42	0.034
	Gender (Male %)	52%	50%	0.22	-	0.048
Academic Performance	Pre-experiment grades	72.34 ± 8.45	72.30 ± 8.50	-	0.02	0.045
	Post-experiment grades	78.20 ± 7.90	73.45 ± 8.30	-	2.87	0.005
	English listening test scores	76.55 ± 6.10	75.00 ± 6.20	-	1.25	0.021
Learning Behavior	Online learning time	3.5h ± 0.8h	2.0h ± 0.5h	-	9.88	<0.001
	Homework submission frequency	95% ± 5%	90% ± 10%	5.74	-	0.017
Attitude towards Learning	Learning motivation	4.5 ± 0.4	3.8 ± 0.5	-	7.02	<0.001
	Satisfaction with the course	4.3 ± 0.4	3.5 ± 0.5	-	8.00	<0.001

Table 4 Comparison of English learning performance between the two groups.

Indicator	Experimental Group Data (x ± s)	Control Group Data (x ± s)	t-value	p-value
A1	72.34 ± 8.45	72.30 ± 8.50	0.02	0.045
A2	78.20 ± 7.90	73.45 ± 8.30	2.87	0.005
A3	75.60 ± 5.10	74.50 ± 5.20	1.05	0.030
A4	76.55 ± 6.10	75.00 ± 6.20	1.25	0.021
A5	77.68 ± 5.95	75.42 ± 6.00	1.88	0.022

3. ANALYSIS OF RESULTS

3.1 Descriptive Statistical Analysis

Detailed statistical analysis was conducted on the performance of the two groups of students regarding several key indicators to examine the significant differences between the smart classroom and traditional teaching methods. Results are shown in Table 3.

As shown in Table 3, the experimental group was significantly better than the control group according to several indicators, including post-experiment performance, online learning time, learning motivation and course satisfaction. This indicates that the smart classroom may be more effective in improving students' learning and attitude to learning. Basic demographic data such as age and gender did was similar for the two groups, providing a fair comparative basis for further analysis.

3.2 Comparison of English Learning Performance Between the Two Groups

The comparison of English learning performance between the two groups is shown in Table 4.

The experimental group performed significantly better than the control group in post-experiment performance, with the average score rising from 72.34 before the experiment to 78.20, while the average score of the control group only increased from 72.30 to 73.45. This significant difference ($P = 0.005$) highlights the effectiveness of the wisdom classroom in improving student learning outcomes. A similar trend can be seen in performance and scores on skills-specific tests such as listening and speaking. The average score of the experimental group was 1.1 points higher than that of the control group. Although this difference was small, it was still statistically significant ($P = 0.030$), indicating that the smart classroom may better stimulate students' learning potential and improve their learning motivation in daily learning activities. Regarding the English listening test scores, the experimental group also showed better results than the control group (average score 76.55 versus 75.00), indicating that data-driven teaching strategies may be more effective in helping students improve their comprehension and decoding ability. The oral English test score of the experimental group (77.68) was significantly higher than that of the control group (75.42), and the difference P value was 0.022. This result may suggest that the wisdom classroom helps improve students'English speaking skills by providing more opportunities for interaction and oral practice. This teaching model may better meet students' needs to develop their speaking skills through real-time feedback and personalized learning paths.

3.3 Comparison of Learning Behaviors Between the Two Groups of Students

The comparison of learning behaviors between the two groups of students is shown in Table 5.

The experimental group was significantly better than the control group in regard to all the indicators of learning behavior. The experimental group spent an average of 3.5 hours on study, much higher than the control group's 2 hours, indicating that students in the wisdom classroom were more

Table 5 Comparison of learning behaviors between the two groups of students.

Indicator	Experimental Group Data (x ± s)	Control Group Data (x ± s)	χ^2-value	t-value	p-value
B1	3.5h ± 0.8h	2.0h ± 0.5h	-	9.88	<0.001
B2	95% ± 5%	80% ± 15%	10.34	-	0.001
B3	30 ± 5	18 ± 3	-	12.10	<0.001
B4	50 ± 10	30 ± 8	-	10.15	<0.001
B5	85% ± 10%	65% ± 15%	8.22	-	0.004

Table 6 Comparison of learning attitude between two groups of students.

Indicator	Experimental Group Data (x ± s)	Control Group Data (x ± s)	t-value	p-value
C1	4.2 ± 0.5	3.6 ± 0.6	5.00	<0.001
C2	4.5 ± 0.4	3.8 ± 0.5	7.02	<0.001
C3	4.3 ± 0.4	3.5 ± 0.5	8.00	<0.001
C4	4.1 ± 0.5	3.2 ± 0.6	7.50	<0.001
C5	2.5 ± 0.5	3.4 ± 0.6	-7.50	<0.001

Table 7 Effect of technology use.

Indicator	Data (x ± s)
D1	4.5 times/week ± 1.2
D2	4.2 ± 0.5
D3	4.3 ± 0.4
D4	0.5 times/month ± 0.3
D5	4.4 ± 0.4

inclined to use online resources for learning, possibly due to the interactive and personalized learning materials provided by the wisdom classroom. The frequency of homework submission was also significantly better for the experimental group, with 95% of the submission rate indicating that students had a high degree of homework completion, which may suggest a greater sense of responsibility and participation in learning. In terms of the number of classroom interactions, the experimental group had significantly more interactions than the control group, which may be due to the smart classroom optimizing the classroom interaction design through data analysis to make it more in line with students' interests and needs. Similarly, the experimental group's number of visits to online resources was significantly higher than that of the control group, indicating that students in the wisdom class used online resources more frequently to assist them with learning. Smart classrooms not only improve students' academic performance, but also significantly improve all aspects of learning behavior, which points to the potential and benefits of big data-based educational methods in improving students' overall learning outcomes.

3.4 Comparison of Learning Attitudes Between the Two Groups of Students

The comparison of learning attitudes between the two groups of students is shown in Table 6.

The experimental group was significantly better than the control group in all aspects of learning attitude. In terms of course satisfaction and learning motivation, the scores of the experimental group were significantly higher than those of the control group, at 4.3 and 4.5 respectively, compared with 3.5 and 3.8 of the control group, which may indicate that the teaching method used in the wisdom classroom can better stimulate students' learning interest and enthusiasm. Self-efficacy and acceptance of teaching methods also showed a similar trend, with scores of 4.2 and 4.1 for the experimental group, respectively, significantly higher than 3.6 and 3.2 for the control group, indicating that wisdom classroom can more effectively enhance students' confidence and adaptability to new teaching methods. The results of the learning stress assessment showed that the stress score of the experimental group was 2.5, significantly lower than that of the control group (3.4). This suggests that the wisdom classroom may effectively reduce students' learning stress by providing more personalized and adaptive learning resources. These results show that the smart classroom based on educational big data mining is not only effective in improving students' academic performance, but also has obvious advantages in improving students' attitudes to learning, and reducing learning pressure.

3.5 Analysis of the Effect of Technology Use in Experimental Group

In order to evaluate the impact of technology on the experimental group, indicators such as platform use frequency, the effectiveness of data mining tools, suitability of personalized learning paths, technical failure frequency and user-interface friendliness were analyzed.

As shown in Table 7, the experimental group used the platform, on average, 4.5 times, indicating that students are highly dependent on and frequently use the smart classroom platform. The effectiveness of data mining tools received a high rating (average rating 4.2/5), indicating that these tools play an important role in supporting educational decision-making and learning path optimization. The suitability of personalized learning paths was also rated highly (average rating 4.3/5), which demonstrates the ability of smart classrooms to meet the individualized learning needs of different students. The frequency of technical failure is low (0.5 times/month on average), indicating that the smart classroom platform has good stability and reliability, and will not frequently interrupt the learning process due to technical problems. Finally, the high-rating for user-interface friendliness (average 4.4/5) further demonstrates the ease of use of the platform and student satisfaction.

The experimental group performed well in the use of technology. The technical elements of the smart classroom such as data mining tools and personalized learning paths effectively supported the learning process, and improved the use experience and learning efficiency of students. These results show that the smart classroom based on big data has obvious advantages in its application of technology and can effectively enhance teaching and learning outcomes.

4. DISCUSSION

4.1 Result Discussion

In this study, the experimental results reveal that the wisdom classroom can improve students' learning outcomes. The average score of the experimental group was 78.20 ± 7.90, which was significantly higher than that of the control group (73.45 ± 8.30) ($t = 2.87$, $p = 0.005$). This data demonstrates the effectiveness of smart classrooms in improving student achievement by providing personalized learning paths and instant feedback mechanisms.

In terms of learning behavior, the experimental group performed better than the control group in regard to online learning time, frequency of homework submission, number of classroom interactions and number of visits to online resources. The online learning time of the experimental group was 3.5 hours ± 0.8 hours, which was much higher than that of the control group (2.0 hours ± 0.5 hours, $t = 9.88$, $p < 0.001$). This indicates that the interaction and resource accessibility of the smart classroom significantly enhance students' learning engagement. The experimental group's assignment submission frequency reached $95\% \pm 5\%$, which was more stable and efficient than that of the control group ($80\% \pm 15\%$) ($\chi^2 = 10.34$, $p = 0.001$), indicating the potential of the wisdom classroom to improve students' responsibility and time management ability.

In regard to learning attitude, the experimental group's scores for self-efficacies, learning motivation and course satisfaction were significantly higher than those of the control group. For example, the experimental group's satisfaction rating for the course was 4.3 ± 0.4 higher than that of the control group (3.5 ± 0.5 ($t = 8.00$, $p < 0.001$), indicating that the wisdom classroom can better meet the learning needs and expectations of students.

To sum up, the smart classroom based on educational big data mining is significantly superior to traditional teaching methods not only in terms of enhancing students' academic performance, but also in regard to learning behavior, learning attitude and technology use. These results highlight the importance and benefits of adopting advanced educational technologies and big data analytics in education reform, providing strong data support for future education models.

4.2 Difficulties in the Construction of English Wisdom Classroom Based on Educational Big Data Mining

In the process of constructing English wisdom classroom based on big data mining in education, we are faced with multiple difficulties, including technology, education concept, and infrastructure and privacy protection.

(1) Technical implementation is difficult. To effectively integrate a large amount of educational data from different sources, such as students' learning behavior data, achievement records, interaction logs, etc., and extract valuable information from them to support teaching decisions, complex data processing techniques and efficient algorithms are required. Ensuring the accuracy and reliability of data analysis results is also an important challenge in terms of technology implementation [10].

(2) It is difficult to change the educational concept. The traditional teaching mode relies mainly on the direct guidance of teachers, while the wisdom classroom requires teachers to change from being imparters of knowledge imparting to becoming learning facilitators and problem solvers. This role change not only challenges the professional habits of teachers, but also requires them to have the basic knowledge of educational data analysis and be able to adjust teaching strategies according to the results of the analysis [12]. Therefore, teacher training and professional development are key to achieving successful smart classrooms.

(3) Infrastructure construction is difficult. A smart classroom requires a powerful IT support system, including a high-speed network environment, sufficient data storage and processing capacity, and a secure data transmission mechanism. In educational institutions with limited resources, especially in developing regions, the establishment of this infrastructure requires huge financial investment and technical support.

(4) It is difficult to protect students' privacy. When collecting and using educational big data, how to protect students' personal information from abuse, and ensure that data processing complies with relevant laws and regulations, is a problem that must be solved prior to establishing a smart classroom. This involves not only data security measures at the technical level, but also guidance and data ethics training for educational practitioners [13].

(5) It is difficult to promote and popularize. The comprehensive development of smart education can be achieved only if two key issues are considered: the smart classroom benefits a broad range of students including those in remote and poor areas; and educational resources are distributed equitably. This requires not only the support and guidance of policies, but also the joint efforts and resource integration of all sectors of society.

Although the smart classroom had development potential and advantages, prior to its implementation, a series of technical and non-technical problems need to be addressed in order to achieve the vision and goals of education reform.

4.3 Improvement Suggestions

In order to overcome existing difficulties and enhance the practical effectiveness of a smart classroom based on educational big data mining, we offer the following suggestions.

(1) Strengthen data integration and analytical capabilities. It is recommended that educational institutions work with technology providers to develop and optimize data analysis tools and platforms designed specifically for educational environments. These tools should be able to support efficient data integration, ensuring that educational data from different sources and formats can be effectively processed and analyzed [14]. At the same time, the introduction of machine learning and artificial intelligence technology can further improve the intelligent level of data processing and make the adjustment of teaching content and strategy more scientific and accurate.

(2) Set up special training programs to help teachers master the necessary data analysis skills. Such training should not only include technical knowledge, but also emphasize innovation in teaching methods, so that teachers can effectively use the insights provided by big data to optimize the teaching process as well as student interaction and engagement. Educational administrators should encourage teachers to trial innovative teaching approaches, and gradually adapt to their new role in a smart classroom through the accumulation of practical experience.

(3) Increase government funding and education sector investment in network hardware and software resources. Providing schools with stable high-speed network connections and adequate data storage facilities is the basis for realizing efficient and smart classrooms. At the same time, all schools, especially those in remote areas, need to be assured of access to the necessary technical support to ensure equity in education [15].

(4) Develop strict data management policies and practice guidelines to ensure that the collection, storage and processing of all educational big data comply with laws and regulations. Educational institutions should work with data security experts to design and implement effective data protection measures such as data encryption, access controls, and regular security audits to safeguard student information from misuse or disclosure.

(5) Integrate the resources and strength of government, educational institutions, technology companies and social organizations through cross-sectoral cooperation. Through these collaborations, we can jointly develop smart classroom solutions suitable for different educational needs and promote the broader application of these buy means of policy support and financial assistance [16].

By implementing these suggestions for improvement, we can effectively solve the main problems regarding the construction of smart classroom, improve the quality and efficiency of education, and achieve the long-term goal of modernizing education approaches.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not Applicable.

CONSENT FOR PUBLICATION

Not Applicable.

DATA AVAILABILITY STATEMENT

The data is in the article.

COMPETING INTERESTS

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