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Innovation and Exploration of Smart Classroom Practice Teaching Mode Based on Artificial Intelligence

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SUMMARY: *Smart classroom is to realize the digitalization and intelligence of classroom teaching with the support of certain information technology and platforms, so that students' learning develops in the direction of comprehensiveness and personalization. Based on artificial intelligence technology, this paper makes reasonable and effective planning for teaching resources and teaching process, and designs a set of smart classroom teaching mode covering before, during and after class. In the current study, the recognition of student classroom behavior technology plays an important role in objectively assessing the quality of classroom instruction. The SVM and IDT algorithms are used to classify the samples of students and training, respectively, and as a result, seven categories of behavior can be recognized, including raising hands, attentiveness to lecturing, writing, standing, reading, sleeping, and mobile phone usage. According to our study, after using the teaching model proposed above, the satisfaction level with AI-based learning resources was up to 78.6%, and the achievements of the students increased from 72.66 to 80.69. The difference between these groups of students was found to be significant compared with a control class with a traditional teaching model ($P < 0.05$).*

KEYWORDS: *Artificial Intelligence; Smart Classroom; SVM; IDT; Classroom Behavior Recognition; Learning Resources Push*

1 Introduction

Since the introduction of the new curriculum reform and the emergence of artificial intelligence, the educational sector has started to acknowledge the need to create a wisdom classroom practice teaching model [1]. The fact that the classroom needs to focus on student gaining wisdom is evident that it does not mean anything else other than creating a learning environment which would involve both knowledge and technology because this is the best opportunity to demonstrate more intelligent teaching methods and make sure that students get personalized teaching services and have a good development experience in the process [2-4].

The intelligent classroom practice-teaching approach makes use of information technology like artificial intelligence, big data, cloud computing, and many more, in addition to the

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application of new teaching approaches and educational logic. This collaboration restructures traditional classroom practices to highlight the possibility of improvement and innovation, thus, leading to an actual increase in the effectiveness of classroom teaching [5-8]. The intelligent classroom is mainly described based on a number of characteristics, including the following: firstly, more focused pedagogy. The intelligent classroom practice-teaching approach overcomes the limitations associated with general education found in the traditional classroom and has better individualized learning capabilities [9]. In the teaching process, it uses accurate pre-classroom material to conduct learning ability evaluation, provides instant assessment and feedback during the official instruction stage, and gives targeted post-classroom exercises based on students' ability, thus realizing the pedagogical goal of educating according to the student's capacity [10-12]. In relation to personalized learning, the existing Literature [13] analyzes the personalized learning phenomenon in the smart classroom environment. With the help of literature review, it determines the possibility of the student-centered approach in terms of providing personalized materials, assessments, and coaching in the smart classroom. Literature [14] considers the personalized learning of English through an artificial intelligence-based practice-teaching model in the smart classroom environment and asserts that personalized learning becomes more efficient due to the usage of a smart classroom. Literature [15] proposes and verifies the "Smart Classroom Environment-Personalized Learning Scale" as reliable in terms of determining the degree of personalization in the process of learning in the smart classroom. Literature [16] highlights the present state of development of smart classrooms and technology tools that contribute to communication between learners and instructors; at the same time, the article provides some smart classroom examples along with the benefits for all the parties involved in educational activities. Literature [17] explores the influence of the smart classrooms on educational practices and discovers that the application of smart classrooms contributes to increasing the engagement of learners in educational activities.

Secondly, classroom engagement has been strengthened. With the continuous advancement of educational informatization, mobile teaching and learning terminals have become more intelligent, enabling diversified forms of communication among teachers and students as well as among learners themselves [18, 19]. Such communication is a central feature of the smart classroom and an effective way to enhance the efficiency of student learning. Literature [20] emphasized the value of smart classrooms in student interaction and pointed out that the rise of these environments has offered a new direction for educational reform. Literature [21] explained that smart classrooms have transformed conventional teaching, especially by fostering intelligence, connectivity, and personalization, largely through sensor technologies, and systematically examined the operational mechanisms of related technologies. In addition, one study investigated the disruptive influence of artificial intelligence on education and conducted a broad review of AI applications in smart classroom interaction, aiming to improve instructional interaction through empirical support and model validation [22]. Another study reviewed relevant research on AI-supported education and identified typical application domains, including automated educational systems and interactive smart classrooms, while also outlining two future research directions that may shape educational policy over the next 25 years [23]. Another study focuses on the feasibility of collaboration and cooperative learning in smart classrooms by means of AI technology, and elaborates on how the AI-based technique increases students' interactivity and gives personalized learning experience to them, thereby indicating that the technique provides an interactive teaching-learning environment that helps greatly improve student performance[24]. Thirdly, feedback based on big data is obtained. In terms of teacher's teaching behavior and student's learning behavior, the practice of instructional modes of the smart classroom contributes to deep digging and accurate analysis using big data, hence overcoming the deficiency in the process evaluation associated with traditional classroom education and providing big-data services to education and teaching [25-28].

In this paper, a smart classroom teaching approach is provided which entails four processes, namely, teaching pre-setting, teaching generation, teaching evaluation, and teaching counseling, carried out using artificial intelligence (AI). The use of feature extraction and classification technologies, including HOG, SVM, LBP, IDT, and artificial neural networks, enables the system to identify behaviors of students in the classroom setting. The identification allows the instructor to evaluate the teaching process and enhance efficiency accordingly. Personalized learning through efficient allocation of learning resources that fit each individual in the smart classroom is possible using AI technology. Academic achievements of students have been improved in this proposed system compared to conventional teaching approaches.

2 Method

2.1 Design of Smart Classroom Teaching Model Based on Artificial Intelligence

The ultimate goal of a smart classroom is to promote students' intelligent generation, and the realization of a smart classroom requires certain conditions, including smart mobile terminals, smart learning technologies, smart learning environments and smart learning resources. In this paper, the teacher's "teaching" and the students' "learning" are further refined into four core links: intelligent teaching presetting, intelligent teaching implementation, intelligent teaching evaluation and intelligent teaching counseling, and a set of closed-loop model covering the whole process before, during and after class is constructed to promote the continuous optimization and development of intelligent teaching in practice. We have constructed a set of closed-loop model covering the whole process before, during and after the class, which promotes the continuous optimization and development of intelligent teaching in practice.

2.1.1 Intelligent Teaching Presets

Under the structure of the smart teaching system, teachers play the key role of pushing resources, while students take the responsibility of independent learning. Intelligent teaching predetermination refers to the use of intelligent tools to assist teachers to carry out detailed and thorough teaching design activities in the pre-course stage. The smart classroom, which relies on the support of artificial intelligence technology, provides teachers with more accurate and personalized teaching materials push services. In the pre-course preparation stage, teachers can make use of intelligent teaching platforms and modern teaching tools such as electronic whiteboards to push diversified and attractive pre-testing resources to students. Students use smartphones, PC terminals and other devices to study and prepare on their own initiative, and submit their pre-study results on their own initiative, so as to stimulate their learning motivation.

2.1.2 Intelligent Instructional Generation

In an AI-based smart classroom, teachers act as the designer and guide of students' learning tasks, driving and promoting cooperative learning among students.Thus, it would be prudent for the educators to carefully prepare questions during classroom lessons, especially those that are directly related to the lives of students, in order to foster their interest, which can help increase the understanding of the students regarding knowledge and life. Moreover, educators can use information technology such as an electronic whiteboard to assign tasks to students' smartphones and tablets, thus making collaboration more productive.

2.1.3 Intelligent Teaching Evaluation

Students are monitored in real time by the Intelligent Assistive System, which evaluates students' individual knowledge and overall learning ability and provides more accurate and efficient learning plans tailored to students' individuality, thus enabling teachers to continuously optimize and adjust the subsequent teaching design. Teachers should fully incorporate students' learning patterns and create a timely opportunity for them to consolidate and promote knowledge transfer. This student-centered teacher-student interaction model not only encourages superior students to actively help intermediate students, but also pays close attention to the learning potential of intermediate students and provides personalized learning support for advanced students to enhance their confidence in learning and strive to narrow the learning gap, which ultimately enhances the overall efficiency and quality of classroom teaching.

2.1.4 Intelligent Teaching Tutoring

Through the intelligent classroom system, which is based on sophisticated artificial intelligence technologies, the learning materials can be provided according to the true level of learning of the students. The teachers can make use of intelligent learning systems to develop customized teaching and counseling schemes for their students. The game mechanism can also be skillfully integrated into intelligent teaching, through the development of scoring mechanisms, the use of fun games, consolidate and improve knowledge. This combination of learning and games not only meets the psychological needs and emotional experience of students, but also helps to stimulate students' interest in learning and further explore their learning potential.

2.2 Smart Classroom Realization Methods

In this chapter, intelligent algorithms are used to facilitate the realization process of the smart classroom and realize the evaluation and direction of smart education by analyzing classroom behavior and providing personalized educational resources.

2.2.1 Classroom Behavior Analysis of Students Based on Artificial Intelligence

(1) Sample classification training

Before realizing the recognition of students' classroom behaviors, it is necessary to collect samples of students' head-up and head-down states and samples of students' behaviors, and train each type of sample separately to generate sample models.

1) Sample training of students' head-up and head-down status: capture samples of students' head-up, head-down and head-around pictures in the video image by manually marking them, normalize the sample pictures to a uniform size, use the HOG feature algorithm to extract features for the three types of samples, and use the SVM algorithm to train the three types of samples to generate the sample model.

2) Student behavior sample training: capture student behavior picture sequence samples in video images by manual marking, apply IDT algorithm to train and classify the samples, and generate student behavior sample model.

(2) Student classroom behavior recognition

Process of identifying student behavior in the classroom is shown in Fig.1. It includes six steps: video compression, head detection, head state recognition, behavior identification, edge detection, and student classroom behavior identification. Actual application of student classroom behavior identification includes collection of video data from the classroom using the camera fixed in the multimedia classroom, reduce the video image according to the equal proportion through the video compression algorithm, detect the head position of each student in the video by using the HOG feature counting and identify the head-up and head-down state of each student in the video, initially determine the body position according to the head position, identify the student's behavior by using the IDT algorithm, the Edge processing is performed on the region near their hands, objects are identified based on the region and shape of the object, and finally the student state is identified by LBP feature algorithm and CNN algorithm, and the overall identification results are summarized to judge and identify the students' classroom behaviors.

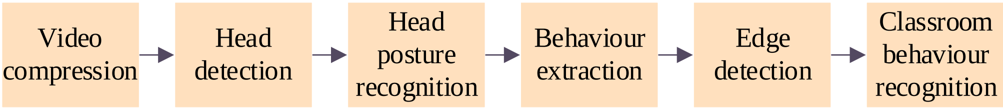

Figure 1: Student classroom behavior identification process

2.2.2 Personalized Learning Resources Push Based on Artificial Intelligence

(1) Learning path planning

For personalized learning materials generated through artificial intelligence systems, the importance of knowledge points is calculated based on their contribution values to the knowledge graph. Using the metric that depends on the contribution values, the most central knowledge points for each course class are determined from the course knowledge graph. These most central knowledge points are then connected to form a network of knowledge points, which is the recommended learning path for the course.

In the course knowledge graph, the contribution value of knowledge points is calculated as follows:

Definition 1: There is a directed acyclic graph $G=(V,E)$ as the topology of the course knowledge graph, where V is the set of knowledge points and E is the set of association relations.

Definition 2: In the course knowledge graph, for a knowledge point i, if there are other knowledge points that have an association relationship with that knowledge point, the predecessor knowledge points and the successor knowledge points that have a distance of 1 from that knowledge point are defined as its 1st-order knowledge points in the topology of the course knowledge graph, and the set of all the 1st-order knowledge points of the knowledge point i is denoted as π_i^1. The precursor and backward knowledge points with a distance of m from this knowledge point are defined as its m-order knowledge points, and the set of all m-order knowledge points of knowledge point i is denoted as π_i^m.

Definition 3: The degree of a knowledge point is categorized into in-degree and out-degree according to the topology of the course knowledge graph, and the in-degree of a knowledge point refers to the set of first-order precursor knowledge points of the knowledge point, denoted by $\Pr e(i)$. The knowledge point out degree refers to the set of knowledge points that are first-order successors of the knowledge point and is denoted by $Suc(i)$.

The contribution value $C(i)$ of a knowledge point is calculated as follows:

$$C(i)=\begin{cases} 1; if \ \left(\left|Suc(i)\right|=0\right) or \left(\left|\Pr e(i)\right|=0\right) \\ \left|Suc(i)\right| \big/ \left|\Pr e(i)\right|; others \end{cases} \quad (1)$$

The centrality of a knowledge point in the course knowledge graph is affected by all the knowledge points in the knowledge graph with which it has an association relationship, and the closer the knowledge points are, the greater the influence.

The calculation method of centrality of knowledge points based on the overall neighbors used in this paper is shown in Equation (2):

$$I_i = \alpha C(i) + \gamma \sum_{j \in \pi_i^1} C(j) + r^2 \sum_{j \in \pi_i^2} C(j) + \cdots + r^m \sum_{j \in \pi_i^m} C(j) \tag{2}$$

where I_i denotes the centrality of knowledge point i. $C(i)$ denotes the contribution value of knowledge point i, parameters α and γ are defined evaluation coefficients, α is the contribution weight of knowledge point i itself, γ is the contribution weight of each order neighboring knowledge point of knowledge point i to the knowledge point i, and in this paper, we consider that the contribution weight of the beginning knowledge point of the same order of the course is the same. $\sum_{j \in \pi_i^m} C(j)$ denotes the sum of the contribution values of all predecessor and successor knowledge points to knowledge point i.

Through the calculation of knowledge centrality in the knowledge graph of the course, it is possible to determine important knowledge points; then, based on their ranking in terms of centrality, we can proceed as follows:

1) According to the topology of the course knowledge graph, extract the set of neighbor nodes of order 1 to m of the knowledge point i without antecedent: $\pi_i^1, \pi_i^2, \cdots, \pi_i^m$.

2) According to the formula (2) for calculating the centrality of knowledge points, calculate the centrality of the 1st order neighboring knowledge points in $\pi_i^1, \pi_i^2, \cdots, \pi_i^m$ respectively, and according to the results of the calculations, filter out the maximum value. If the knowledge point with the largest centrality is not selected after the computation of the 1st order neighbor knowledge points is completed, the centrality of the 2nd order neighbor knowledge points in $\pi_i^1, \pi_i^2, \cdots, \pi_i^m$ is continued to be computed, and the computation is continued in accordance with the method, and finally the centrality of the $\pi_i^1, \pi_i^2, \cdots, \pi_i^m$ in the knowledge point with the largest centrality.

(3) Filter out the knowledge points with the largest centrality in $\pi_i^1, \pi_i^2, \cdots, \pi_i^m$ computed in step 2, and link the filtered knowledge points according to the order of the strata of the course knowledge graph, and the resulting link of knowledge points is the recommended course learning path.

(2) Personalized Learning Resources Push

For implementing personalized learning resources recommendation consistent with the course learning path, relevant learning resources associated with particular knowledge points are recommended to the learner based on his/her personalized learning path. Making use of the data collected through the developed student model, the system offers relevant test questions focused on knowledge points. Estimating the failure rate of the student in regard to particular knowledge points, the system updates the representation of knowledge points by taking into account their centrality scores.

1) Initialization of Student User Knowledge Points Lost Score Rate

Definition 4: The loss rate of test questions refers to the ratio of the number of points that a student user loses by completing a test question with errors and the full score of the test question.

Assuming that the test trial completed by student user S_i is denoted as $T_{S_i}^Z$, $Z \in 1, 2, \cdots, M$, and the loss of points for completed test trial is recorded as $\phi_{S_i}^Z$, the vector of the loss of points for all completed test trial by student user S_i is shown in Eq. (3):

$$\phi_{S_i} = \left(\phi_{S_i}^1, \phi_{S_i}^2, \cdots, \phi_{S_i}^M\right) \tag{3}$$

Definition 5: The failure ratio of a knowledge point is the ratio of the sum of the failure rates of the knowledge point test questions completed by the student user to the total number of exercises completed by the student user.

The ratio of the sum of the failure rate of the test questions of the knowledge point K_N completed by the student user and the total number of all the exercises completed by the student user is denoted as $R_{S_i}^{K_N}$, and the vector of the failure ratios of the N knowledge points completed by the student user S_i during the learning process is shown in Eq. (4):

$$R_{S_i} = \left(R_{S_i}^{K_1}, R_{S_i}^{K_2}, \cdots R_{S_i}^{K_N}\right) \tag{4}$$

Definition 6: The rate of occurrence for a knowledge area is the ratio between how often that knowledge area shows up in the test questions answered by the student user and the number of test questions answered.

Assuming that student user S_i has completed a total of α test questions, the occurrence rate of knowledge points K_N in the α test questions completed by student user S_i is denoted as $P_{S_i}^{K_N} = \frac{\sum_1^{\alpha} T_{s_i}^z}{\alpha}$, then the vector of occurrences of N knowledge points learned by student user S_i is shown in Equation (5):

$$P_{S_i} = \left(P_{S_i}^{K_1}, P_{S_i}^{K_2}, \cdots P_{S_i}^{K_N}\right) \tag{5}$$

Definition 7: Knowledge point failure rate refers to the ratio of the knowledge point failure ratio to the occurrence rate of the knowledge point in the process of completing the course by the student user. Its calculation formula can be expressed as $f_{S_i}^{K_N} = \frac{R_{S_i}^{K_N}}{P_{S_i}^{K_N}}$, and it can be seen from Eq. that the matrix of N knowledge points lost points ratio learned by U student users is shown in Eq. (6):

$$F = \begin{Bmatrix} f_{S_1}^{K_1} & \cdots & f_{S_1}^{K_N} \\ \vdots & \ddots & \vdots \\ f_{S_U}^{K_1} & \cdots & f_{S_U}^{K_N} \end{Bmatrix} \tag{6}$$

In this paper, the method of calculating the knowledge point loss rate is to calculate the loss rate of knowledge points that are independent of each other, and $f_{S_i}^{K_N}$ denotes the loss rate of student user S_i in completing the test exercises that contain the knowledge point K_N.

(2) Updating the missing point rate by using the centrality of knowledge points

According to the formula (2) in the previous section for calculating the centrality of knowledge points, the contribution value between knowledge points is calculated, and $W\left(K_a, K_b\right)$ denotes the contribution value of the knowledge point K_b to the knowledge point

K_a, and the evaluation coefficients in the formula (2) are taken to be $\alpha = 1$, $\gamma = \frac{1}{2}$, then the formula for $W(K_a, K_b)$ is as follows:

$$W(K_a, K_b) = C(K_a) + \left(\frac{1}{2}\right)^m C(K_b) \tag{7}$$

where m denotes that the knowledge point b is an m-order neighbor of the knowledge point a, then the lost score rate of the knowledge point a is updated as $\left(f_{S_i}^{K_a}\right)'$, calculated as follows:

$$\left(f_{S_i}^{K_a}\right)' = f_{S_i}^{K_a} + f_{S_i}^{K_b} W(K_a, K_b) \tag{8}$$

The updated matrix F' of lost points for N knowledge points learned by U student users is shown in Equation (9):

$$F' = \begin{Bmatrix} \left(f_{S_1}^{K_1}\right)' & \cdots & \left(f_{S_1}^{K_N}\right)' \\ \vdots & \ddots & \vdots \\ \left(f_{S_U}^{K_1}\right)' & \cdots & \left(f_{S_U}^{K_N}\right)' \end{Bmatrix} \tag{9}$$

The analysis of the failure rate of a particular knowledge point for a learner will be used to check if the knowledge mastery by the learner for that particular knowledge point meets the criteria required. Afterward, learning materials related to those knowledge points will be delivered to the student.

3 Results and Discussion

In this study, teaching practices are conducted in a school that has all the required hardware and software infrastructure, which provides ideal conditions for conducting an intelligent classroom teaching approach. The participants of this research include two different classes taught by the same English teacher, where one is considered as the experimental group (n=40) following the intelligent classroom teaching approach and the other is the control group (n=40).

After the two-month experiment, the behavior of a particular group within the two classes was observed and analyzed, and a survey of questionnaires was conducted to obtain feedback from the learners regarding their level of satisfaction with the learning tools used. The purpose of this was to investigate whether the behavior of the learners and the recommended learning tools were well received by the learners when exposed to different methods of instruction. Both classes were tested for the subject matter before and after the experiment.

3.1 Analysis of Students' Classroom Behavior

Based on artificial intelligence for students' classroom behavior recognition, seven specific behaviors including raising hands, listening to lectures, writing, standing, reading, sleeping and playing cell phones can be identified eventually.

Under different teaching modes, the classroom behaviors of students in the experimental class and the control class are shown in Figure 2, (A1~A7) denoting the above seven classroom behaviors, respectively. In the smart classroom teaching mode, one person in the experimental class showed the behavioral performance of sleeping and playing cell phone respectively, while in the traditional teaching mode, four and one students in the control class showed the behavioral performance of sleeping and playing cell phone respectively. The percentage of the experimental class who stood up to answer questions was 1.2% less than the percentage of hands raised, indicating that the experimental class answered most of the questions actively, while the percentage of the control class who stood up to answer questions was 10.2% more than the percentage of hands raised, indicating that the control class answered most of the questions passively.

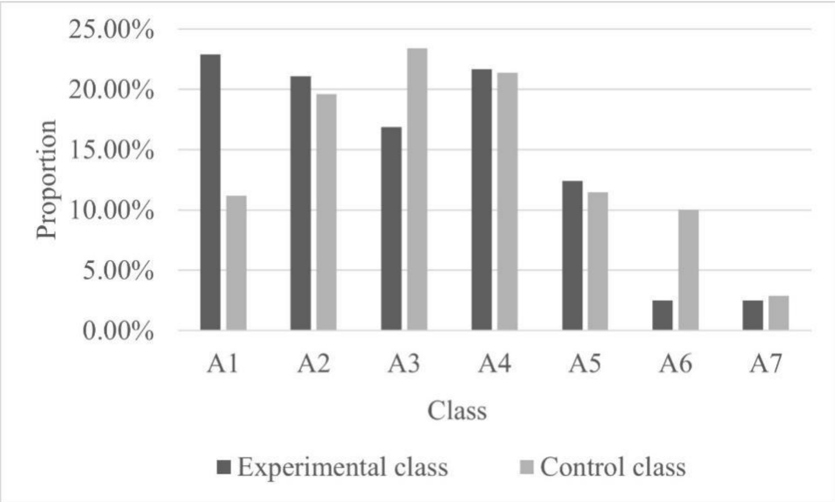

Figure 2: The performance of the students

3.2 Learning Resources Satisfaction Survey

This scale has five levels of satisfaction, namely "very satisfied," "quite satisfied," "average," "not too satisfied," and "very dissatisfied." The scores for each level are 5, 4, 3, 2, and 1, respectively. The total number of questionnaires issued was 80, and all 80 questionnaires were retrieved, resulting in an effective retrieval rate of 100%.

The satisfaction survey of learning resources in experimental and control classes under different teaching modes is shown in Figure 3. The learning resources chosen by all students in the experimental class are pushed by artificial intelligence, and their satisfaction rate reaches 78.6%. In the control class, all the students used learning resources recommended by teachers or chosen by themselves, and their satisfaction rate was only 28%. Most of the students thought that the learning resources recommended by teachers or chosen by themselves were not targeted and did not have a clear learning direction and goal.

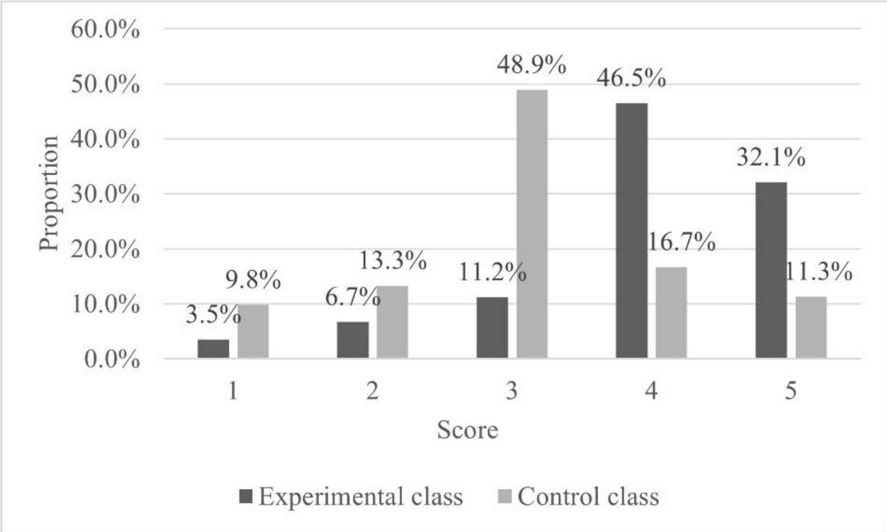

Figure 3: Study resource satisfaction survey

3.3 Comparative analysis of teaching models

3.3.1 Analysis of students' pre-test scores

The percentage of the number of students in each score band in the two classes before the start of the experiment is shown in Figure 4. The difference in the number of students on each score band between the experimental class and the control class is small, with the same number of students in score bands 80-90 and 60-70, 7 and 8, respectively.

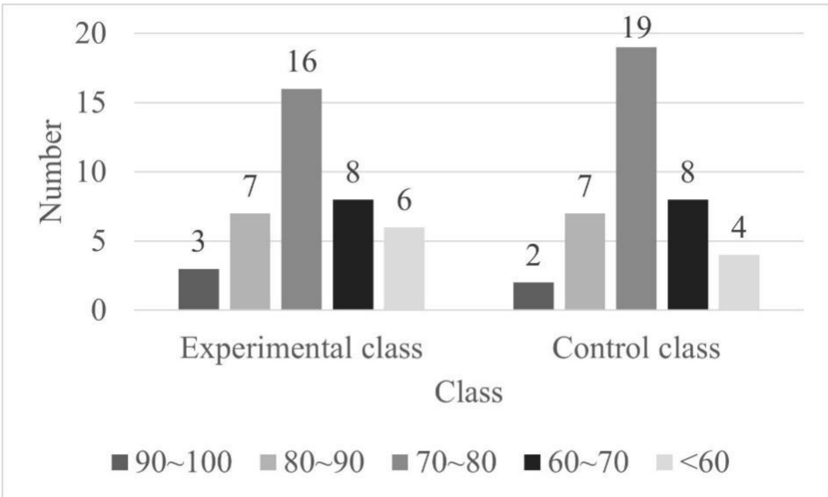

Figure 4: The number of people in each section is the ratio of pretest

The average grades of the students in the experimental and control classes are shown in Figure 5. The average grades of the two classes are 72.66 and 72.37 respectively, and the difference between the average grades of the two classes is 0.29, which is a small difference, thus indicating that the two classes are at a comparable level of learning.

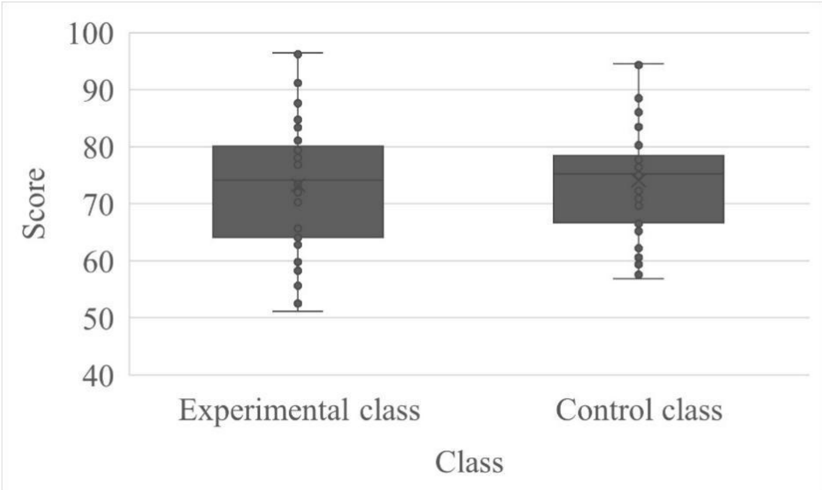

Figure 5: Student performance statistics of pretest

The grades of the sample were subjected to an independent samples t-test, and the results are shown in Table 1 below. The significance of the F-test is 0.85, which is higher than 0.05. Thus, while testing the sample based on the assumption of equal variance (isotropic variance), the two-tailed significance is 0.852, which is much higher than 0.05. Hence, there is no significant difference between the means of the grades of the two groups. This means that the students in the experimental group and control group can be considered as similar populations.

Table 1: Independent sample t test of pretest grade

Pretest grade	Levene variance equivalence test		Average equivalent t test						
	F	Sig.	t	Freedom	Sig (2-tail)	MD	SED	The difference is 95% confidence interval: Lower limit	Upper limit
Assumed equal variance	0.224	0.85	0.133	92	0.852	0.332	2.52	-3.241	4.251
Unassuming equal variance	-	-	0.133	93.524	0.852	0.332	2.53	-3.242	4.252

3.3.2 Analysis of student post-test scores

After completion of the experiment, students of both experimental and control groups were tested for their understanding of the experimental instruction materials. The number distribution among score groups for both groups is shown in Figure 6. From the results, it can be seen that there is a considerable change in the number distribution among score groups for the experimental group, since the number of students who scored 90-100 increased from three to five, while the number of students who scored 80-89 increased from seven to 16. Also, there were no students who scored less than 60 points.

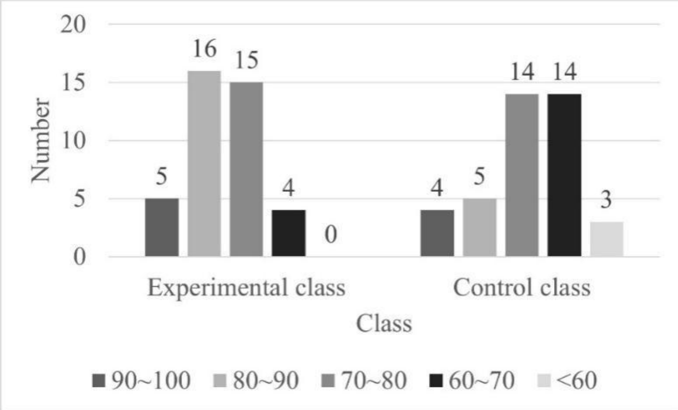

Figure 6: The number of people in each section is the ratio of posttest

Statistics of post-test scores of the two groups are presented in Figure 7 below. The experiment group obtained a mean score for the knowledge test that is 6.63 points higher compared to that of the control group. It is clear that their performance is significantly better. These results imply that the intelligent classroom teaching method using AI is beneficial to students' academic performance.

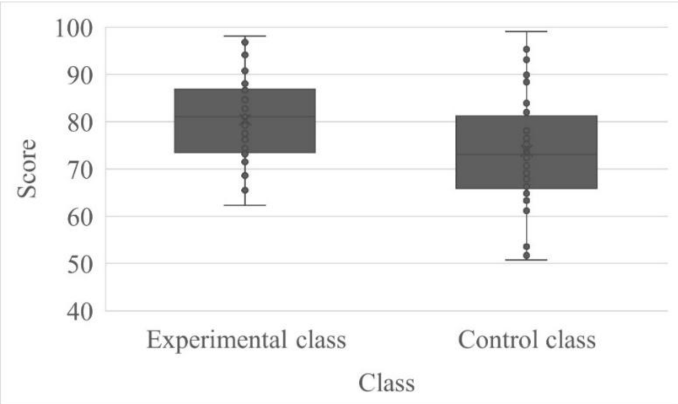

Figure 7: Student performance statistics of posttest

The result of the independent sample t-test conducted on the collected data using SPSS has been summarized in Table 2 below. After comparing the scores of knowledge test obtained by the experimental group and control group, a p-value of 0.011 was obtained, showing statistical significance at the $p<0.05$ level, meaning there was a significant difference in learning performance of the two groups. These results show that the intelligent classroom model of teaching performs better because it incorporates artificial intelligence.

Table 2: Independent sample t test of posttest grade

Posttest grade	Levene variance equivalence test		Average equivalent t test						
	F	Sig.	t	Freedom	Sig(2-tail)	MD	SED	The difference is 95% confidence interval	
								Lower limit	Upper limit
Assumed equal variance	1.536	0.213	2.563	90	0.011	4.723	1.836	1.022	8.241
Unassuming equal variance	-	-	2.563	89.632	0.011	4.723	1.825	1.025	8.236

Through teaching experiments, it was found that when using the smart classroom teaching mode based on artificial intelligence, students' classroom behavior was more positive compared to the traditional classroom mode, and students were more agreeable to the recommended teaching resources, and the application of this mode for practical teaching significantly improved students' performance in just two months.

4 Conclusion

Intelligent classroom teaching, based on the use of artificial intelligence, is composed of several key elements such as intelligent teaching presetting, intelligent teaching generation, intelligent teaching assessment, and intelligent teaching consultation. In these elements, student classroom behavior identification and the application of personalized learning resources prove critical for teachers to have a complete picture of the learning environment and improve the quality of classroom teaching. When compared to traditional teaching strategies, the intelligent classroom teaching strategy results in an increased number of students voluntarily raising their hands for speaking (9), reduced cases of sleeping in classrooms (1), high satisfaction with learning resources (78.6%), and an increase in student performance by an average of 6.63 points. The intelligent classroom teaching strategy suggested by this study presents an insightful approach to analyzing the learning environment and providing students with improved and personalized learning experiences.

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About the Author

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