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Strategies for Enhancing the Interactivity of IoT Communication Teaching Empowered by Swarm Intelligence Algorithms

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Abstract To enhance the interactivity of IoT communication teaching, this paper utilizes data mining and swarm intelligence algorithms to establish an interactive teaching platform, aiming to extract valuable information from large-scale behavioral data during the teaching process. Strategies for improving teaching interactivity are proposed from technical, adult student, and school perspectives. Taking a group of students from a certain university as the research object, the empirical results show that the distribution of interaction indices for students at the university follows an “L” shape. Most teachers and students have interaction indices below 20, with a small portion ranging from 40 to 60. After applying the interactive teaching platform, there was a significant difference in performance between Class A and Class B at the 0.05 level.

Index Terms swarm intelligence algorithms, data mining, teaching interaction, IoT communication teaching

I. Introduction

The Internet of Things (IoT) is a rapidly developing new information technology that enables the interconnection of all things, meaning that people, machines, and objects can communicate with each other anytime and anywhere [1], [2]. This technology is an interdisciplinary field that encompasses multiple disciplines such as communications, computer science, automation, electronics, and sensing technology, with a wide range of applications. Among these, communication technology serves as the bridge for information exchange within IoT systems and is the foundation for realizing IoT applications [3]. As a result, many universities offering IoT engineering programs have introduced IoT communication technology courses in recent years. These courses aim to provide students with a comprehensive and systematic understanding of the basic principles, architectural frameworks, and typical applications of various communication technologies in an IoT environment [4]. As one of the core courses in IoT engineering programs, it employs a teaching approach that integrates theory with practice, equipping students with the foundational skills required for design, development, application, and management in IoT-related fields, thereby providing a critical pathway for students to gain a deeper understanding of the IoT domain [5]. The content of IoT communication technology courses covers various types of communication network architectures, existing network communication technologies, and communication protocols, resulting in a broad and diverse range of knowledge points, making it challenging for students to absorb the material. Additionally, traditional teaching methods primarily involve teachers imparting knowledge in the classroom, emphasizing theory over practice and lacking teacher-student interaction, which hinders students' ability to actively engage in learning and fosters a lack of initiative and depth in their thinking [6]-[8]. Furthermore, the lack of practical application is primarily due to the scarcity of virtual experimental environments and the high cost of specialized teaching equipment, making it difficult for students to engage in effective real-world simulations and classroom interactions [9]. Meanwhile, interactive teaching has become a demand sought by nearly 90% of students [10]. It is evident that the absence of interactivity in IoT communication education is a significant issue.

Swarm intelligence algorithms are a class of optimization algorithms based on swarm intelligence, which simulate various group behaviors and intelligence in nature to solve complex problems. In swarm intelligence algorithms, cooperation and communication among individuals in a group are simulated to achieve global optimal solutions or approximate optimal solutions, such as ant colony optimization algorithms and particle swarm optimization algorithms [11], [12]. Swarm intelligence algorithms are widely applied in the field of education. Reference [13] applied the ant colony optimization algorithm and an ant colony optimization algorithm with selection probabilities to optimize university course scheduling. The latter not only achieved the highest performance and reduced computational costs but also obtained the optimal solution. Reference [14] constructed an ant colony optimization algorithm-driven adaptive tutoring system that personalizes based on student needs and characteristics, provides optimal learning paths, and embeds a feedback loop to implement dynamic adjustments to provide students with the optimal learning path, thereby tutoring students in their learning. Reference [15] utilized a leapfrog evolutionary ant colony optimization algorithm to construct an online personalized learning path recommendation model with features such as speed, accuracy, high quality, and real-time interaction. Literature [16] uses a discrete particle swarm optimization algorithm to evenly distribute teaching information resources, solving for optimal resource weights, allocation methods, and allocation ratios, with a response time of less than 3.2 seconds. Literature [17] discusses the application of swarm intelligence algorithms and their improved versions in educational data analysis, which can solve for optimal learning paths, automatically classify data, and predict student performance. These studies provide practical references for the transferable application of swarm intelligence algorithms to enhance teaching interaction.

Addressing issues such as the low accuracy of traditional data mining, this paper primarily utilizes the particle swarm algorithm—a swarm intelligence optimization algorithm—to improve inertial weights, accelerate algorithm convergence, and optimize data mining techniques. Furthermore, the K-means clustering algorithm is employed to prevent results from getting stuck in local optima. Using the optimized data mining techniques, this paper designs and implements an interactive teaching platform comprising two parts: teaching platform data statistics and teaching platform data analysis. Students from the Internet of Things Communication major at a certain university are selected as the research subjects to analyze the interaction between teachers and students and the effectiveness of the teaching platform.

II. Data mining optimization methods

Data mining is user-centric, with a focus on reading and analyzing data information during human-computer interaction. In the process of data mining and management, implicit and unknown knowledge and rules that have potential value for decision-making are extracted from the data warehouse. When analyzing the data mining process and its practical applications, the focus is on controlling aspects such as data information processing, knowledge application, and algorithm complexity from the perspectives of data mining management and information processing, thereby achieving data mining and extraction.

From a theoretical perspective, the data mining process includes knowledge classification, knowledge display, data mining model construction, knowledge practicality evaluation, and knowledge extraction and application. By implementing in-depth management and control of data mining information, the overall effectiveness of data mining can be enhanced. From a technical application perspective, data mining includes data preprocessing, data visualization, and the application of data mining algorithms. Based on an assessment and analysis of existing data information, calculations are performed from the perspectives of data knowledge and data mining management to comprehensively enhance the effectiveness of data mining. The application domains and system development of data mining vary, leading to differences in data mining effectiveness in practical applications. Data mining extracts effective processed data from large amounts of noisy random data. In actual applications, it features real-time processing of massive data, random queries for user-required data, and predictions for markets with little or no historical data. Under the premise of achieving data mining and data relationship analysis, it enables effective processing and control of data information.

Regarding algorithm recommendations, intelligent algorithms and IoT communication course teaching exhibit coupling characteristics. On one hand, intelligent algorithms utilize data mining and deep learning technologies to precisely deliver information to users, enhancing teaching interactivity and providing technical support for precise teaching in IoT communication courses. On the other hand, intelligent algorithms possess instrumental rationality and require value guidance and regulation from IoT communication to achieve value rationality and healthy development. In the process of deep integration, intelligent algorithms can provide technical support for IoT communication course teaching reforms. By analyzing student behavior data, they can accurately grasp students' ideological trends, positively influencing precise teaching in IoT communication courses. However, algorithms also bring risks and challenges.

IoT data is input into the algorithm, with random initialization of population, cluster centers, and various parameters. The K-means clustering algorithm is applied to calculate the clustering objective function, particle fitness values, and update individual extrema, global extrema, cluster centers, particle velocity, and particle positions. If the algorithm's calculation results reach the optimal value or the maximum iteration count, the algorithm terminates; otherwise, it continues to iterate, updating the cluster centers, particle velocities, and positions to obtain the optimal data mining results. The data mining method is shown in Figure 1.

During the analysis of the data mining steps, it is a multi-stage process based on loops and repetition, and through basic data mining information control, the effectiveness of data mining processing is enhanced. The data mining process is as follows:

(1) Analyze the data mining requirements and clarify the expected relationships, thereby determining the appropriate data mining algorithm.

(2) Under the premise of processing data information, control from the perspectives of data preprocessing and data transformation, and control based on data objectives. After establishing data objectives, improve data quality and control from the perspectives of data mining and data variables.

(3) Under the premise of data mining and processing, data mining technology can be applied to enhance the effectiveness of data mining.

(4) Under the premise of analyzing data visualization information, improvements are made from the perspectives of data information processing and information control, thereby comprehensively enhancing data processing effectiveness.

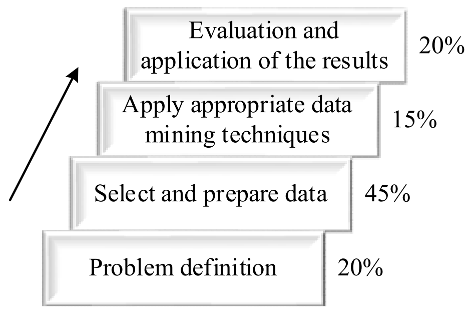

Figure 1: Data Mining Process

II. A.Improving the particle swarm algorithm

The particle swarm algorithm is a classic swarm intelligence optimization algorithm that simulates a flock of birds hunting by initializing a dataset as a particle swarm. Each particle represents a bird in the flock and has two attributes: velocity and position. The velocity and position expressions of the particles are shown in Equation (1):

$$\begin{cases} x_i = (x_{i1}, x_{i2}, \cdots, x_{id}) \\ v_i = (v_{i1}, v_{i2}, \cdots, v_{id}) \end{cases} \tag{1}$$

In this context, d denotes the dimension of the search space, x_i represents the position of particle i, and v_i denotes the velocity of particle i. After initializing the particle swarm, the fitness value of each particle is calculated. The particles continuously update their velocity and position (flight direction) based on the calculated fitness value until the optimal value that satisfies the conditions is found or the maximum number of iterations is reached, at which point the algorithm terminates. The formula for calculating the fitness value of a particle is shown in Equation (2):

$$\begin{cases} x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \\ v_{id}^{t+1} = \omega v_{id}^t + c_1 r_1 (P_{id}^t + x_{id}^t) + c_2 r_2 (P_{gd} + x_{id}^t) \end{cases} \tag{2}$$

In this context, t denotes the number of iterations, while x_{id} and v_{id} represent the position and velocity of particle i in the d th dimensional space, respectively. It can be observed that the velocity formula v_{id} consists of three components: the continuation component, the individual learning component, and the social cognition component. $\omega(0 < \omega < 1)$ represents the inertial weight for inheriting the current velocity. The larger this value, the stronger the algorithm's global search capability; the smaller this value, the stronger the algorithm's local search capability. The individual learning component represents the particle's local search capability, where c_1, r_1 denote the learning factor and random function of the individual cognitive component, respectively, and $P_{i\omega}^t$ denotes the optimal position of particle i in the d th dimension of space. The social cognitive component represents the global search capability, i.e., information sharing among particles. c_2, r_2 represent the learning factor and random function of the social cognitive component, respectively, and P_{gd} denotes the global optimal position of particle i in the d th dimensional space. Since the selection of the inertia weight ω has a significant impact on the convergence performance of the algorithm, an adaptive inertia weight calculation formula is introduced, as shown in Equation (3):

$$\omega = \begin{cases} \omega_{\min} + \dfrac{2}{\pi}\arctan\left[\dfrac{\pi(\omega_{\max} - \omega_{\min})}{T}\right], 04 \le \omega \le 09 \\ \omega_{\max}, 09 < \omega < 1 \end{cases} \tag{3}$$

When the inertia weight is small, the iterative results of the algorithm approach the global optimum value of the particles plus the individual optimum value, thereby effectively improving the convergence speed of the global optimum. Therefore, a smaller inertia weight can be set during the early iterations of the algorithm to ensure its local learning ability, and a larger inertia weight can be set during the later iterations to ensure its global optimization performance [18].

II. B.K-means clustering algorithm

The particle swarm algorithm performs a global random search. Compared with other swarm intelligence algorithms, this algorithm has the advantages of being easy to operate, low complexity, and fast execution speed, making it well suited for processing IoT data. However, this algorithm is prone to getting stuck in local optima when approaching the optimal solution, resulting in poor convergence. To prevent the algorithm from getting stuck in local optima and improve its convergence, an improved K-means clustering method is incorporated after the initialization of the particle swarm algorithm, effectively combining the particle swarm algorithm with the K-means clustering algorithm.

The particle swarm algorithm with clustering not only initializes velocity and position but also transforms the initialization of the particle swarm into the clustering centers $C = (C_1, C_2, \cdots, C_k)$. The K-means clustering objective function is shown in Equation (4):

$$fit = \frac{1}{1 + \sum_{j=1}^{k} \sum_{X_i \in C_j} \| X_i - B_j \|} \tag{4}$$

In this formula, C_j denotes the jth cluster, X_i denotes a particle in cluster C_j, B_j denotes the cluster center of cluster C_j, and k denotes the number of clusters. This formula calculates the discrete value of a particle using the Euclidean distance function, where a larger discrete value corresponds to a smaller adaptation value.

II. C.Algorithm Steps

The specific calculation steps of the mining algorithm based on swarm intelligence algorithms are as follows:

(1) Initialize the N data points in the dataset as particles, initialize the cluster centers, and initialize the velocity and position of the particles. Randomly initialize the particle swarm.

(2) Send the updated particle swarm into the K-means clustering algorithm. By calculating the distance between the particles and the cluster centers, after several iterations, update the cluster centers, the individual extrema of the particles, and the global extrema.

(3) By continuously updating the particle velocities, after several iterations, obtain the updated particle swarm, velocities, and positions.

(4) If the algorithm's calculation results meet the conditions or reach the maximum number of iterations, the final results are output; otherwise, the process returns to step 2 to continue iteration.

III. Establishment of an interactive teaching platform

Based on the aforementioned swarm intelligence algorithms, this project designed and implemented an interactive teaching platform.

The teaching platform data mining system consists of two parts: teaching platform data statistics and teaching platform data analysis. The teaching platform data statistics part includes two modules: exam analysis and student behavior statistics. The exam analysis module collects students' exam scores for courses and then displays the statistical results in graphical form. The student behavior statistics module records students' activities within the platform, including system login frequency, login duration, participation in group discussions, participation in forum discussions, total number of questions asked, and total number of course materials viewed, providing a data foundation for the teaching platform's data analysis [19]. The data analysis section of the teaching platform includes two modules: course question hot keywords and student behavior analysis. The course question hot keywords module records, organizes, and analyzes the fields that students ask questions about and search for during the course Q&A process, extracting the top ten course keywords that students are most concerned about. Teachers can also view the latest questions related to these keywords. The system architecture design is shown in Figure 2.

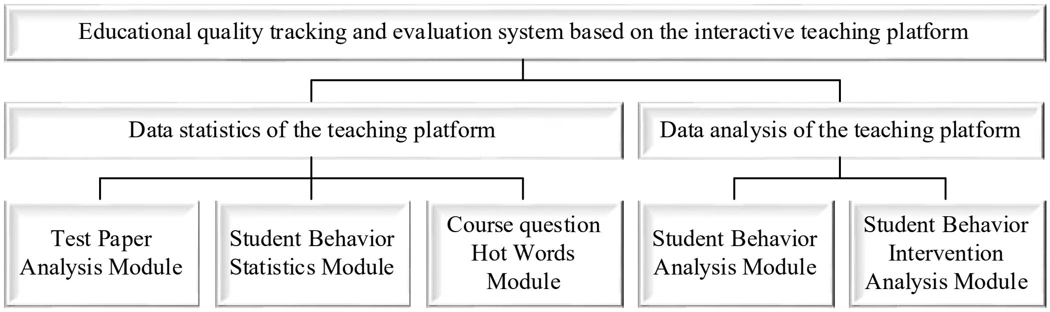

Figure 2: System Architecture Design

To enhance the security and scalability of the data mining system on the teaching platform, the software system is implemented using the popular Struts 2.0 and JDBC frameworks. The Struts framework is an application framework that integrates the advantages of Java Servlet and JSP technologies, serving as a classic scalable application of the MVC design pattern. JDBC provides platform-independent access control for various relational databases.

Database tables are used to store system records of student user grades, interactive behaviors, and analyzed results data. The database primarily includes the following tables: student user login information table, student user forum interaction information table, student user group discussion interaction information table, student user interactive Q&A information table, student user question search information table, student user behavior analysis table, and course question hotword table. The student user login information table records detailed information such as student usernames, login times, and logout times. The student user question information table records information such as the time the student user asked a question and the course number. The student user forum interaction information table records information such as the time the student user posted on the forum, the title, the content, the course number the post was targeted at, whether the post was replied to, and the total number of posts made by the student user. The Student User Group Discussion Interaction Information Table records the time of creation and participation in group discussions, course information, and the total number of group discussions participated in by student users. The Student User Question Search Information Table records the time of searches conducted by student users within the interactive teaching platform, search content, and click-through rates of search results. The Student User Behavior Analysis Table records the results of data mining analysis conducted on each student by the data mining system: the level of platform activity engagement by student users and predicted course grades for student users.

IV. Analysis of experimental results

IV. A. Application Examples

Classroom data mining analysis is a highly complex system engineering task involving massive amounts of data, complex algorithms, and various applications. We have already compiled a comprehensive research report based on actual application data. Due to space constraints, we will use the analysis of the teacher-student interaction index in smart classrooms as an example to describe a typical data mining analysis application scenario.

The real-world data used in this study was sourced from a university student population that routinely used the system, accumulating a large amount of process behavior data and academic outcome data, providing a robust big data foundation for this study's data analysis. To protect student privacy, anonymous coding was applied to the data during analysis.

IV. A. 1) Basic Framework for Mining Analysis

Teacher-student interaction is the core of classroom interaction and an important feature that distinguishes IoT communication classroom teaching from traditional teaching. Enhancing interaction between students and teachers helps to increase students' engagement in learning and improve their motivation. Based on data mining of classroom teaching behavior in IoT communication classrooms, analyzing and researching teacher-student interaction indices can comprehensively and objectively demonstrate the interaction between teachers and students, thereby providing a basic basis for designing and improving classroom teaching interaction.

IV. A. 2) Selection of interactive indicators

The establishment of indicators is the foundation for the construction of the entire indicator system. In order to comprehensively and objectively reflect the interaction between teachers and students, we followed the principles of practicality, development, comprehensiveness, and feasibility when selecting indicators.

IV. A. 3) Construction of indicator weights

Different behavioral indicators can reflect the interactive relationship between teachers and students in various aspects. Directly analyzing these behavioral indicators would be overly complex. Factor analysis can integrate variables with complex relationships into a smaller number of factors, thereby reproducing the interrelationships between the original variables and the factors. It is a statistical method used in multivariate statistics for dimension reduction.

Using the sociological statistical software SPSS for factor analysis, principal component analysis and orthogonal rotation were applied to the original 16 variables. The results of factor extraction based on principal component analysis are shown in Table 1.

Table 1: Factor extraction of main component analysis

Constituent	Initial eigenvalue			Rotate the squares and load		
	Tot	Variance contribution	Cumulative contribution	Tot	Variance contribution	Cumulative contribution
1	7.235	45.21875	45.21875	3.915	24.46875	24.46875
2	1.925	12.03125	57.25	3.528	22.05	46.518
3	1.722	10.7625	68.0125	2.887	18.04375	64.56175
4	1.216	7.6	75.6125	1.689	10.55625	75.118
5	1.069	6.68125	82.29375	1.127	7.04375	82.16175

Using the weights of the aforementioned teacher-student interaction indicator system, the interaction index between each teacher and student can be calculated, where n represents the number of behavioral indicators. After calculating the interaction index between teachers and students, it is normalized between 0 and 100. The distribution of interaction indices for students at a certain university is shown in Figure 3. The teacher-student interaction index follows an “L”-shaped distribution, with only a small proportion of teacher-student interaction indices exceeding 40 or 60, while the majority of teacher-student interaction indices are below 20.

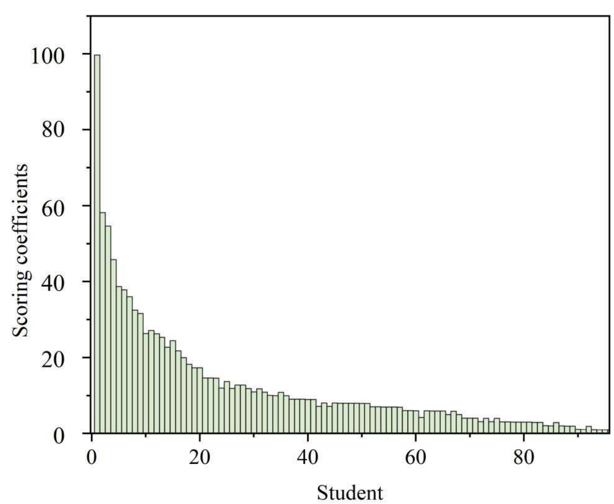

Figure 3: Teacher and student interactive index bar chart

Based on the above research, we found that the teacher-student interaction index follows an “L” distribution. Specifically, by comparing the original indicators with the constructed interaction index, we discovered that, in general, teachers who upload more micro-lessons and those with higher-quality micro-lessons tend to have higher interaction indices with students. The mean interaction index in the high-interaction group was 30.735, 8.896 in the medium-interaction group, and 4.308 in the low-interaction group. Therefore, teachers need to upload and share high-quality micro-lessons and continuously improve their online teaching methods to enhance interaction with students.

IV. B. Comparison of teaching effectiveness

This study selected two classes from the Internet of Things Communication major at a certain university to conduct a one-month teaching experiment using an interactive teaching platform. Class A had 40 students, and Class B had 40 students. To ensure consistency in the learning levels of the two classes, the midterm test scores of the two classes were selected as pre-test scores for comparison and analysis. The analysis results are shown in Figure 4.

Class A had an average score of 62.38, with a standard deviation of 19.14, while Class B had an average score of 63, with a standard deviation of 20.96. The differences in mean scores and standard deviations between the two classes were small. The results of the independent samples t-test indicated that the p-value for the t-test of the test scores between Class A and Class B was $P = 0.967 > 0.05$, indicating that there was no significant difference in the pre-test scores between Classes A and B at the 0.05 significance level. Based on the above analysis, selecting Classes A and B for the practical study provides good comparability and can serve as control classes for the experiment. Class B was randomly selected as the control class, where the lecture review mode remained the traditional method, with teachers selecting incorrect questions based on subjective experience for a full-class review, and students primarily passively listening. The other class, Class A, serves as the experimental class, where the review lesson employs a teacher-student interactive model supported by big data for review instruction.

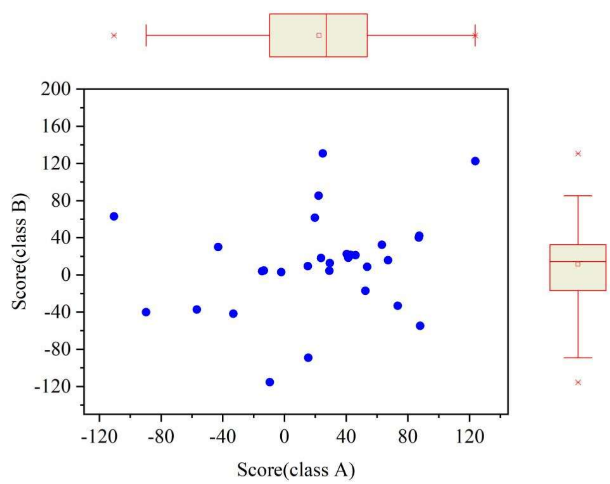

Figure 4: Compared with the two class test scores after practice

The improvement in academic performance of students in the experimental class and the control class after the application of the method was evaluated through the final exam. The growth in academic performance between the two classes before and after the application of the method served as the basis for assessing the effectiveness of the method. The comparison of academic performance between the two classes is shown in Figure 5. In terms of academic performance, there was a significant difference between the experimental class and the control class after the intervention. The experimental class achieved an average score that was 12.16 points higher than the control class. A comparison of the average scores before and after the intervention revealed that the experimental class demonstrated a significantly greater improvement in academic performance than the control class.

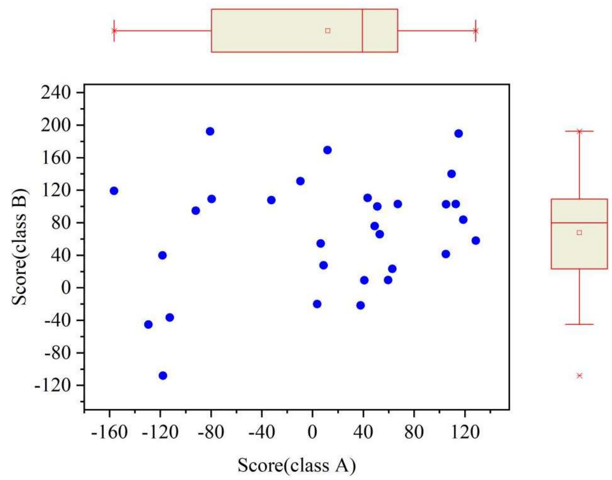

Figure 5: The results of two classes were compared before and after practice

The results of the pre- and post-test performance comparisons between the two classes are shown in Table 2: The post-test P-value for Class A and Class B was P = 0.038 < 0.05, indicating that there was a significant difference in performance between the two classes at the 0.05 level. Overall, the application of this model had a certain promotional effect on student performance growth. However, this teaching model constrained students' innovative abilities and imagination. In smart classroom teaching, one can leverage the smart classroom information platform to enhance teacher-student interaction, thereby breaking away from traditional teaching models. By analyzing teacher-student interaction behaviors, one can calculate the teacher-student interaction index and evaluate teachers accordingly.

Table 2: Comparison of performance of two class tests

Class	Experimental average score (before)	Experimental average score (After)	The average difference is the average difference
Class A	62.38	85.9	23.52
Class B	63	75.16	12.16
P value	0.967	0.038	

IV. C. Strategies for improving the effectiveness of teaching interaction

(1) Leverage technology to support and optimize the teaching environment.

Fully utilize the advantages of intelligent algorithms to promote the integrated development of education, upgrade online open education hardware and software, and enhance online open education teaching support services. Introduce cloud service platforms and mobile teaching smart terminal devices to build a smart education platform for open education, providing centralized, intelligent, and immersive support services for open education. Use interactive classroom software and various smart tools to stimulate adult students' interest in learning, increase their engagement, and enable them to deeply participate in the teaching process, achieving immersive interactive effects.

(2) Play the leading role of teachers, formulate appropriate teaching

(3) Emphasize the central role of students, and improve interaction participation rate and engagement.

Rely on intelligent algorithms to enhance students' proactive awareness, promote student-to-student interaction, student-to-teaching resource interaction, and student-to-learning environment interaction.

V. Conclusion

This paper utilizes swarm intelligence algorithms and K-means clustering-related algorithms to enhance the accuracy of data mining technology and establish an interactive teaching platform. Taking students majoring in Internet of Things (IoT) communication at a certain university as the research subjects, the study explores the interactive relationship between teachers and students as well as teaching effectiveness. The results show that the interaction index between teachers and students in the IoT communication program at the university exhibits an "L"-shaped distribution. Most teachers and students have low interaction indices, concentrated below 20, with relatively few indices in the 40–60 range. Using an independent samples t-test, it was found that there was a significant difference in test scores between Class A and Class B after the interactive teaching platform was applied.

Based on this, strategies to improve teaching interactivity were proposed from technical, adult student, and school perspectives.

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