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The Design and Implementation of an Intelligent Education Prototype for an Electronic Systems Course*

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The rapid development of big data and artificial intelligence has brought impact on every aspect of people's lives. However, college students' education is still relatively traditional in that all students receive the same instruction, which hinders the improvement of students' performance. Students need more personalized teaching based on fast-developing technology. This paper introduces the design and implementation of an intelligent education prototype for an electronic systems course, and 89 students were given customized learning based on this prototype. The intelligent education prototype is based on the teaching platform to assist education. On the one hand, it provides students with various teaching resources. On the other hand, it makes statistical analysis based on the behavior data of students on the platform, so as to assist teachers in adjusting teaching strategies. To verify the effectiveness of our teaching method, we compared these students' final scores with the scores of other students who used traditional teaching methods. Student performance is assessed using examination results. The results indicate that the average score of the students who used the intelligent education prototype is 6.3 points higher than those who used the traditional teaching mode. The prototype proposed in this paper provides a reference for improving online education and is expected to positively influence the teaching of other courses in the future.

Keywords: data analysis and visualization; electronic systems; intelligent education; personalized learning

1. Introduction

With the extensive use of network technology and multimedia, developing education and research services on the network has become a development trend in teaching in recent years [1, 2]. Students can study by themselves through network and exchange learning information. It can help students to improve their learning interest and learning effectiveness. In particular, the emergence of the COVID-19 virus has severely affected teaching in many schools. In this situation, the distance education develops rapidly [3, 4].

There are already a number of online learning platforms, such as Coursera, Udacity, edX and FutureLearn, which are also known as Massive Open Online Courses (MOOCs). These platforms integrate a large number of teaching resources and provide convenience for students' learning. However, they often do not make full use of students' learning behavior data, resulting in failure to feedback to teachers about students' learning in time.

To solve this problem, we designed and implemented an intelligent education prototype based on big data and artificial intelligence technology for an electronic systems course. The prototype can make full use of the online learning behavior data of students, and through visualization and data analysis, it can not only assist students find their own weaknesses, but also help teachers understand the learning situation of students, so as to adjust teaching strategies in time. This paper describes the overall design and implementation details of the education platform for an electronic systems course, and tests the effectiveness of the intelligent education prototype through the actual investigation results.

The remainder of this paper is organized as follows. In Section II, we introduce related works about education platforms. In Section III, we explain the system's architecture. In Section IV, we discuss our implementation of the prototype. In Section V, we report our experimental setup and results. Finally, we conclude the paper and discuss directions for future work in Section VI.

2. Literature Review

2.1 Problems of Traditional Education

In recent years, the science and technology in the field of big data and artificial intelligence has improved dramatically. However, the college students do not fully enjoy the convenience brought by big data and artificial intelligence technology, and the classroom education is still in a relatively traditional mode. The face to face methods of teaching (direct methods) such as lecture, demonstration and discussion, have gradually failed to meet students' learning needs.

There are many problems with traditional educa-

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tion. First of all, the knowledge is still mainly taught by teachers. However, students' learning ability is different, so the traditional teaching model can only adopt the same teaching method and content for all students, and it is impossible to teach students according to their aptitude. Secondly, the homework is still set in the same way, that is, each student completes the same homework. The direct consequence of this is that students with poor self-control may copy each other's homework, while excellent students reflect that the homework questions are too simple and hope to do more challenging questions. Finally, using the traditional teaching model, teachers cannot obtain the students' learning situation in a timely and comprehensive way, which affects the adjustment of teaching strategies to a certain extent. Therefore, there is an urgent need to improve traditional education.

In higher education, some of the factors that influence students' academic achievement include teaching methods, learning style, and student workload. However, literature and some researchers have made it known that integration of technology into classroom instruction if appropriately implemented have strong and positive impact on students' achievement [5–7]. Based on the above problems, more and more online education platforms have emerged. The popular MOOC platforms such as Coursera, Udacity and edX have become today's most popular education systems, with modules such as video courses, documents, interactive learning activities and quizzes [8]. In addition to these MOOC platforms, many universities and colleges have developed and constructed their own education platforms. New technologies to improve the performance of the teaching platform will be introduced next.

2.2 Technologies to Facilitate Education Effectiveness

In order to improve the performance of these teaching platforms, many new technologies have been gradually applied to the platform construction. Data mining is a commonly used technology to improve the teaching quality of the platform. Yunus Santur [9] presented an approach based on machine learning and big data for the online education systems to offer student-specific learning activities. Shishi Chen [10] constructed an ideological and political teaching resource integration platform based on big data to solve the problem that the traditional ideological and political teaching resource integration platform could not keep up with the rapid resource integration in the era of big data. Yuan Jiugen [11] built an online interactive education platform model, and improved the efficiency of online interaction between teachers and learners through the analysis of platform functions and data mining. Manikandan [12] gave classification and prediction results of students' performance using machine learning tools. Reeping [13] leveraged historical transcript data to visualize student trajectories within the individual courses.

In addition, virtual reality is also a new technology often used in the construction of teaching platforms. For example, Lin Li [14] constructed an online virtual experiment teaching platform, visualized abstract concepts in a database technology and application course, and completed the sharing and promotion of virtual experiment resources. Baiqiang Gan [15] built an online professional teaching resource library platform for virtual simulation, which combines the characteristics of immersion and interaction in virtual reality technology.

Finally, there are game elements, cloud computing and other new technologies used in the construction of the teaching platform. Yumang [16] developed a website that applies game elements to academics, which provides a new teaching and learning experience. Huijuan Lu [17] proposed a teaching platform based on cloud computing, analyzed the feasibility of the platform, and demonstrated its overall functional achievements and implementation. Yuli Deng [18] proposed a personalized learning platform specifically designed for hands-on computer science labs in a cloud environment, which can identify learning styles based on student activities and adapt learning material accordingly.

Although these platforms bring convenience to students' learning, there is still no platform specifically for the electronic systems course. What's more, there is still plenty of shortcomings in the current platforms. For example, many of these platforms ignore the exploring the students' behavior data in depth, and they are not comprehensive enough in the aspects of visualization and personalization, so there is still a lot of boost spaces. In view of this situation, we designed and implemented an intelligent education prototype for the electronic systems course. The basic functions of the intelligent education prototype include resource sharing, homework, online communication, online examination and so on. In addition, compared with other platforms, there are more perfect visualization functions, and provide personalized exercises recommendation for students. Finally, the effectiveness of the teaching method based on the intelligent education prototype is verified by experiments.

3. System Design

The system architecture of the intelligent education prototype is shown in Fig. 1. Students log in to the

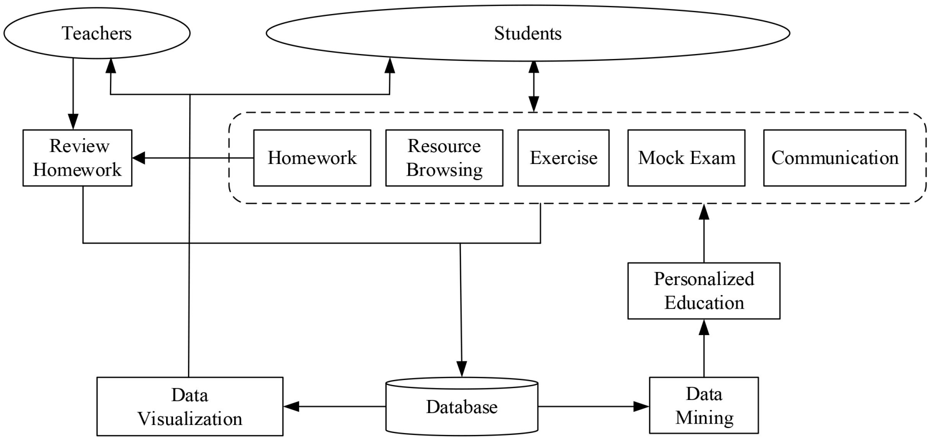

Fig. 1. The system architecture of the intelligent education prototype.

intelligent education platform through a Web browser. On the platform, they can submit homework, browse learning resources, do exercises, take mock exams and communicate. The student-generated behavioral data on the website, such as visiting times, browsing time and exercise answers, will be collected and stored in the database. The homework needs to be graded by teachers and then the scores will be stored in the database. After that, through the analysis and visualization of the collected data, the visual results of students' learning can be fed back to teachers and students to help them make timely adjustments. At the same time, according to the data mining of the student behavior data in the database, the prototype can analyze students' weaknesses and then recommend appropriate exercises or videos to provide students with personalized education.

4. Implementation of the Prototype

The platform is based on the B/S technology framework. The backend of the platform is based on the Flask framework, while the front end is mainly based on HTML, CSS, and JavaScript. MySQL was used as the data management system. The development language is Python 3.7.0. The specific details of the platform are as follows.

4.1 Resource Construction

There are mainly four types of resources on this platform, namely video, exercise, courseware, and homework. The number and clicks for each type of resource are shown in Table 1. The video, which is recorded by the students and released after being reviewed by the teachers, explains some of the course's knowledge points or sample exercises. The exercises were selected from the exercise bank. The teachers provide the courseware and homework, according to the course schedule.

On this basis, we labeled each resource to generate corresponding characteristic data. Take the exercise resource for example, we stored the chapter of the exercise, knowledge points, and other related information in the corresponding characteristics database. Furthermore, students' data with regard to these resources can be used to generate a knowledge graph of the course.

4.2 Database Design

The database tables are mainly divided into two categories. The first category contains static tables that record users' personal data, resource data, exercise data, and homework data. The other category contains dynamic tables that record interactions between users and the platform. The specific details are shown in Fig. 2.

4.3 Data Analysis and Visualization

This prototype can obtain students' behavior data and visualize it. Students can clearly recognize their own individual situations from the feedback from the website, which can help them identify their own weaknesses and take action to improve. At the same time, teachers can also get the overall learning situation of the class through visualization, which can help them adjust teaching strategies in time to improve the teaching quality. The visualization of students' behavior data is on the browser side, and pie charts is used to generate graphs, including bar

Table 1. The number of and clicks for each type of resource

	Type	Number of resources	Number of clicks
1	Video	63	6135
2	Exercise	282	1007
3	Courseware	24	3750
4	Homework	30	1026

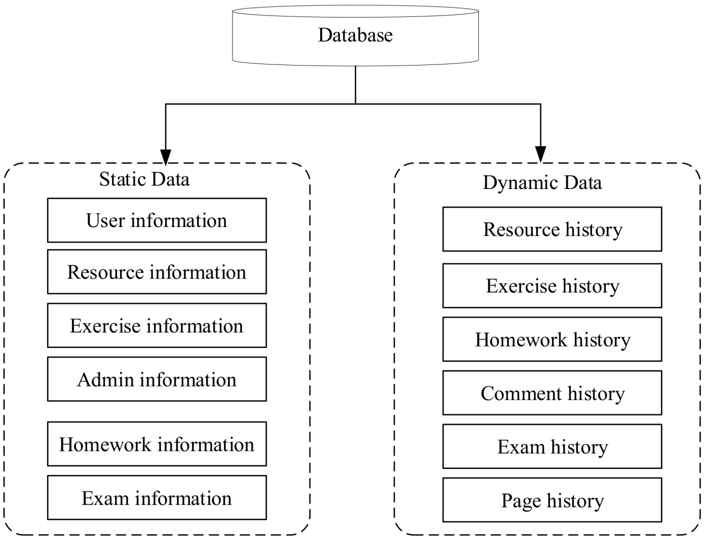

Fig. 2. The architecture diagram of the database.

graphs, line graphs, pie graphs, heat diagrams, and radar graphs. The visualization mainly includes six aspects, namely video, homework, exercise, class overview, resource browsing, and ability portrait. More details are as follows:

4.3.1 Video

The students' video-watching situation has been visualized on the platform, including the number of visitors, video evaluation, and hot videos. The hot videos of the month viewing situation is shown in Fig. 3. The hot videos of the month are the five most visited videos in the last 30 days. The two columns show the number of visitors and collection times of each video in the last 30 days, and the broken line represents the average score of each video given by students. As can be seen from Fig. 3, the video numbered Chap4_2 has been visited by 51 students and collected by 1 student in the last 30 days. The average evaluation score of the video is 4 points.

4.3.2 Homework

Homework submission in the electronic systems course is completed on the platform. Since homework is assigned weekly as the course progresses, data visualization of homework is calculated on a weekly basis. For each week's homework, six aspects were counted: the distribution of homework submission, submission time, score, finishing time, students' feedback on homework difficulty, and students' error type. The distribution of homework submission overview is shown in Fig. 4, in which the horizontal axis represents each homework exercise,

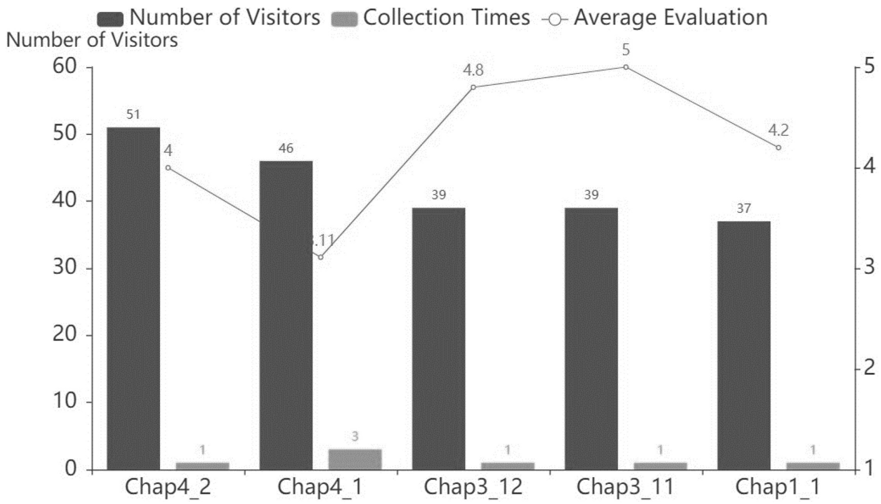

Fig. 3. The hot videos of the month viewing situation.

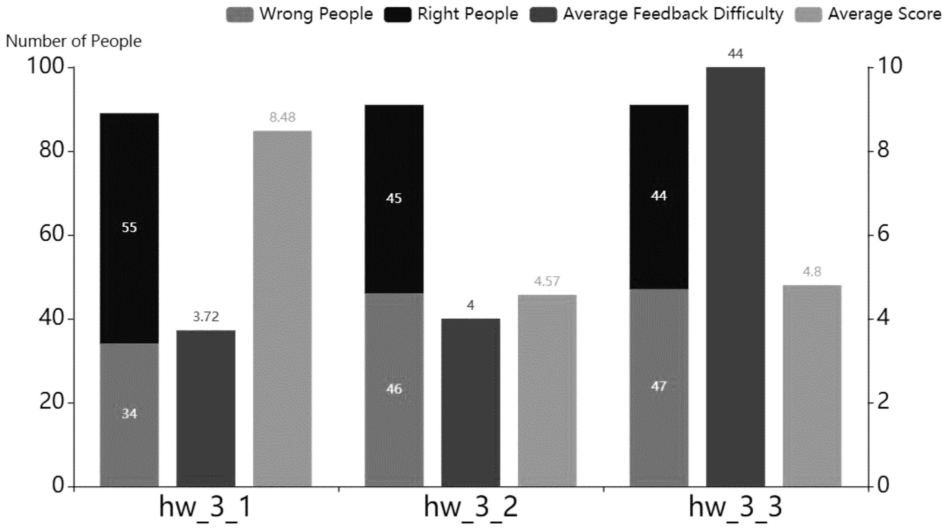

Fig. 4. The distribution of homework submission overview.

and the vertical axis represents the correct number, wrong number, average feedback on difficulty, and average score of each homework exercise. As can be seen from Fig. 4, for the homework exercise numbered hw_3_1, 55 students answered correctly, and 34 students answered wrong. The average feedback difficulty score is 3.72 out of 5, and the average score of this exercise is 8.48 out of 10.

4.3.3 Exercise

The situation of students' exercise completion has been visualized on the platform, including the correct rate of exercises, feedback on homework difficulty, and the popular exercises completion situation. The hot exercises of the month completion situation are shown in Fig. 5, in which the horizontal axis represents each exercise, and the vertical axis represents the correct number, wrong number and average feedback on difficulty of each exercise.

4.3.4 Class Overview

The usage data of all the students in the class have been showed on the platform, including homework score, homework completion time, average homework submission time, exercise completion situation, comments, resource browsing times, etc. In addition, the student's personal data are attached to the figure to allow students to compare themselves with the class' overall situation. The resource browsing quantity is shown in Fig. 6, in which the horizontal axis represents the quantity interval, and the vertical axis represents the number of students corresponding to the quantity interval. The upper

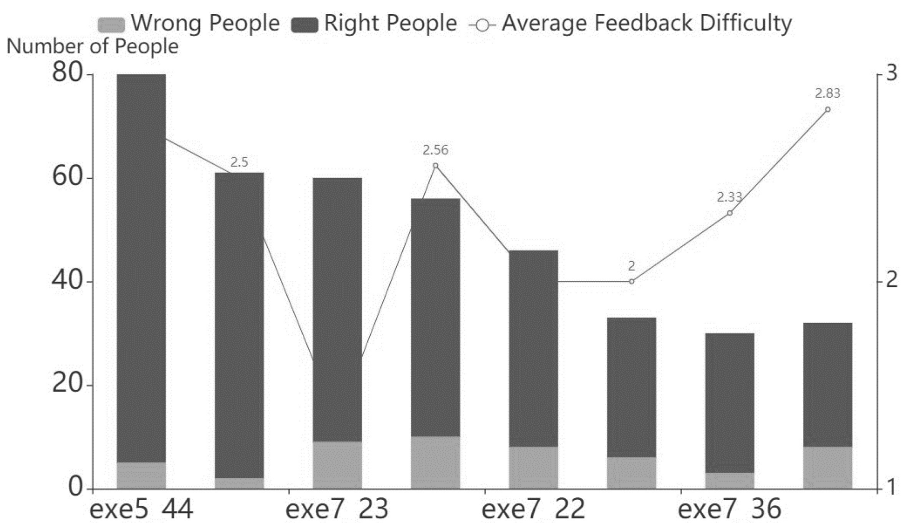

Fig. 5. The hot exercises of the month completion situation.

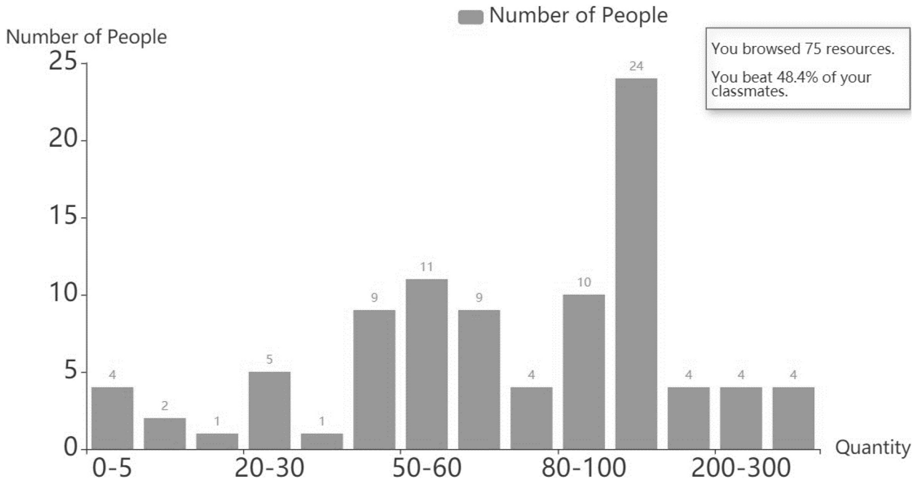

Fig. 6. A histogram showing resource browsing quantity.

right corner shows the student's personal data. This student has browsed 75 resources, and he exceeds 48.4% of the students.

4.3.5 Resource Browsing

Resource browsing has been visualized on the platform, including different chapters' resource browsing proportions and changes in visits over time. The students' resource browsing proportions for different chapters are shown in Fig. 7, in which different colors represent different sections. There are four sub-graphs in Fig. 7. The upper left graph represents individual video browsing proportions for different chapters, and the upper right graph represents the video browsing proportions of the class. The lower left graph represents individual completed exercises proportions for different chapters, and the lower right corner represents completed exercises proportions of the class. As can be seen from Fig. 7, chapter 3, chapter 5, and chapter 7 account for the largest percentage, indicating that these chapters are relatively important. This finding is indeed consistent with the actual situation. The change in video browsing times is shown in Fig. 8, in which the horizontal axis represents the week, while the vertical axis represents the visits. The top line represents the number of visits, and the bottom line represents the number of visitors. Since the course lasts for 18 weeks, we only count the 18-week visits. It can be seen that the number of visits was the largest in the 18th week. We analyze that the reason is that there was the final exam in the 18th week and students began to concentrate on review, resulting in a significant increase in visits.

4.3.6 Ability Portrait

As shown in Fig. 9, the radar map is used to display the students' ability portraits. The larger the area of the radar map is, the stronger the student's capability has. The student's situation and the average class situation are displayed on the same radar map

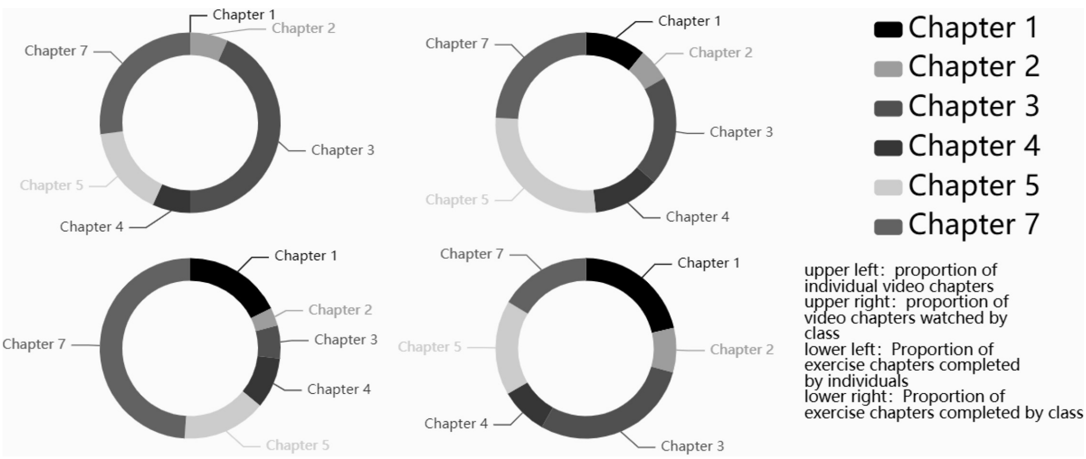

Fig. 7. Resource browsing proportion by chapter.

Fig. 8. Changes in the number of video visits.

for comparison between each individual student's level and the class' average situation. The eight indicators on the radar map are correct homework rate, homework score, homework completion speed, homework submission speed, number of completed exercises, correct exercise rate, resource browsing, and number of comments.

4.4 Personalized Recommendations

This platform recommends personalized exercises for students according to their learning conditions. The recommendation process is shown in Fig. 10. The exercise recommendation system's input data includes both dynamic and static data. The dynamic data are the students' historical behavior data. Since not all the data from the students' behavior dataset is meaningful, the students' behavior data must be preprocessed. Static data refers to the exercise resource, which should be structured first. Based on the input data, we can recommend exercises using an iterative algorithm. After recommending exercises, students can compensate for their individual weaknesses and may discover new weaknesses. Further analysis of students' weaknesses means that students will constantly receive recommendations of new exercises that can help them improve their mastery of the knowledge points.

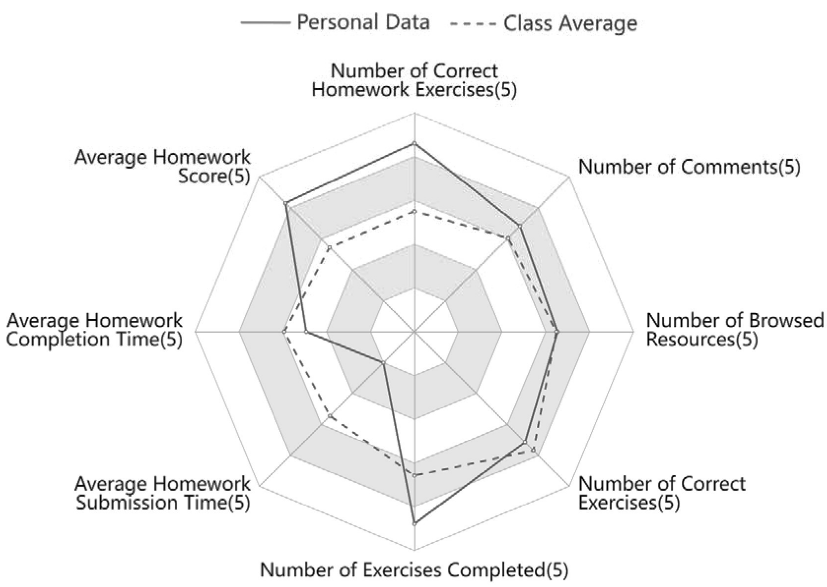

Fig. 9. A student ability portrait.

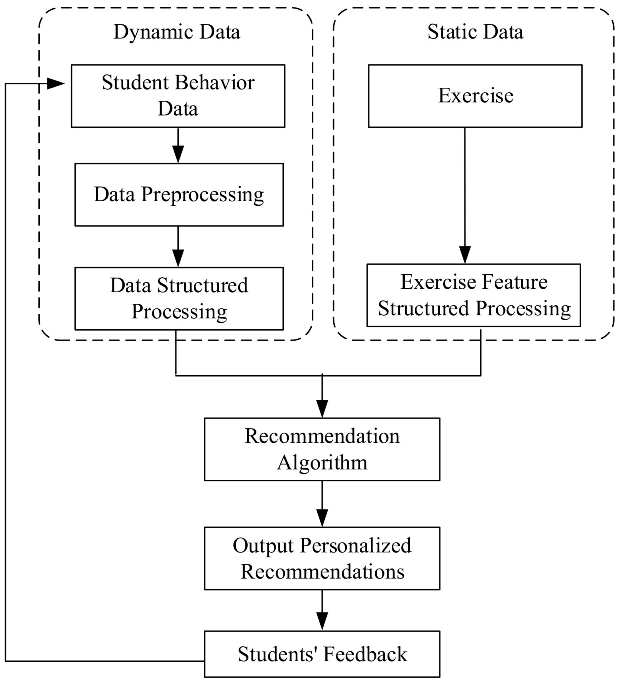

Fig. 10. A flow chart showing the personalized recommendation process.

5. Results and Discussion

5.1 Experiment Setup

(1) Participants: The participants were 178 students from a joint program at Queen Mary University of London (QM) and Beijing University of Posts and Telecommunications (BUPT).

(2) Duration: This was a 4-month experiment in the spring semester of 2020.

(3) Target course: This experiment aimed at the electronic systems course.

(4) Content of the experiment: During the experiment, we divided the 178 students into a treatment group and a control group, with 89 students in each group. The students in the treatment group were required to complete their homework using the platform. They were free to select other functions, such as resource browsing and mock examination. The data on the platform were collected and recorded in the database, and other useful data were also collected through questionnaires. Finally, the students' collected data were analyzed. The students in the control group received traditional teaching without using the platform.

5.2 Student Behavior Analysis of the Treatment Group

We mainly used cluster analysis, classification analysis, and correlation analysis to analyze student behavior, and the results have been visualized locally. From the above analysis and the visualization of student behavior, a clear understanding of the students' overall situation can be obtained, which can help teachers identify problems in a timely manner and improve teaching quality.

5.2.1 Cluster Analysis

We grouped students from different perspectives. The first perspective is shown in Fig. 11, which presents the students' cluster analysis results based on the correct homework rate and diligence, in which the correct homework rate refers to the correct number of homework exercises and diligence is the number of browsed resources and the number of completed exercises. The horizontal axis represents the normalized diligence index, the vertical axis represents the normalized correct homework rate, different shaped points represent different categories, and the pentacles represent cluster centers. By analyzing the cluster analysis results shown in Fig. 11, it can be found that students are mainly divided into three categories: students who are not trying hard but have high accuracy rates, students who are not trying hard and have low accuracy rates, and students who are trying hard and have high accuracy rates. Those who are trying hard but have low accuracy rates do not exist. This indicates that the homework difficulty level is relatively reasonable, and students will not get a low score if they spend more time doing homework.

The second perspective pertains to the students' clustering results based on the correct homework and correct exercises rates, in which exercise accuracy refers to the rate of correctly completed exercises. The clustering results are shown in Fig. 12. The horizontal axis represents the correct exercise rate, and the vertical axis represents the correct homework rate. It can be seen from Fig. 12 that the students are mainly divided into four categories. The first category consists of those with a high rate of both correct exercises and correct homework. This category is the largest, indicating that the correct exercise rate can, to a certain extent, reflect the situation of correct homework. The second category contains students with a high correct exercise rate but a low correct homework rate. Further analysis of these students' situation shows that they complete fewer exercises but have a high correct rate. In the third category, students' correct exercise rate is low, but their correct homework rate is high, indicating that this kind of student did not seriously complete the exercises, though they completed the homework with more meticulousness. The fourth category contains students with low rates of both correct exercises and correct homework, which indicates that a minority of students did not work hard.

With the cluster analysis, teachers can find the students in need of help. For example, students who do not work hard and have a low correct rate of homework are likely to fail in the exam. Teachers can take some measures to encourage these students to complete more exercises so as to get good grades. In addition, students with high accuracy in homework are excellent students, and teachers do not need to pay too much attention.

5.2.2 Classification Analysis

The CART decision tree algorithm was used to classify students. Students with a final exam score above or equal to 60 were identified as ordinary, and students with a final exam score below 60 were identified as at risk. The input parameters of the decision tree are average homework score, number of browsed resources, number of correct exercises,

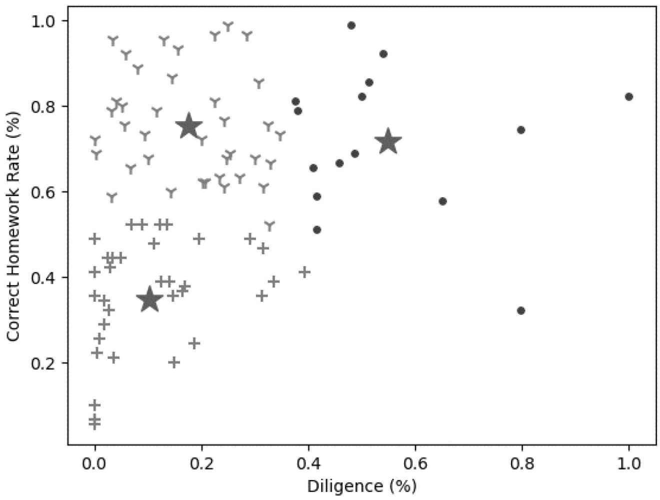

Fig. 11. Cluster results based on the correct homework rate and diligence.

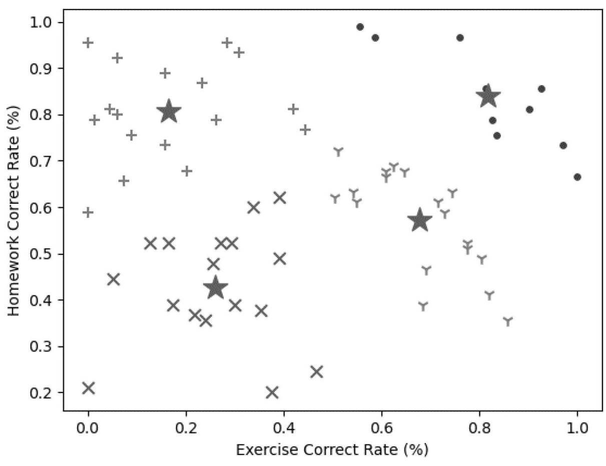

Fig. 12. Cluster results based on the correct homework and correct exercises rates.

number of mock exams taken, and average homework completion time. The final decision tree is shown in Fig. 13. It can be seen from Fig. 13 that the most important factor is the average homework score, followed by the number of browsed resources. This indicates that the average homework score can reflect the final exam results to a certain extent. In addition, through this model, teachers can predict in advance the students at risk who may fail in the future and give timely help to improve the performance of these students.

5.2.3 Correlation Analysis

We used the Apriori algorithm to analyze the relevance of the course knowledge points. Each exercise consisted of no more than three knowledge points. Let the knowledge points be A, B, and C to form the knowledge point group. The knowledge point group of the exercises is taken as the input of the Apriori algorithm, and the output is the support degree of the knowledge point group, including the support degree of each knowledge point and the support degree between knowledge points. The visualization of the correlation between knowledge points is shown in Fig. 14. The size of each point represents the degree of knowledge point support, and the greater the degree of knowledge point support, the larger the shape of the point. The connection between the points indicates that the connected knowledge points are likely to be inves-

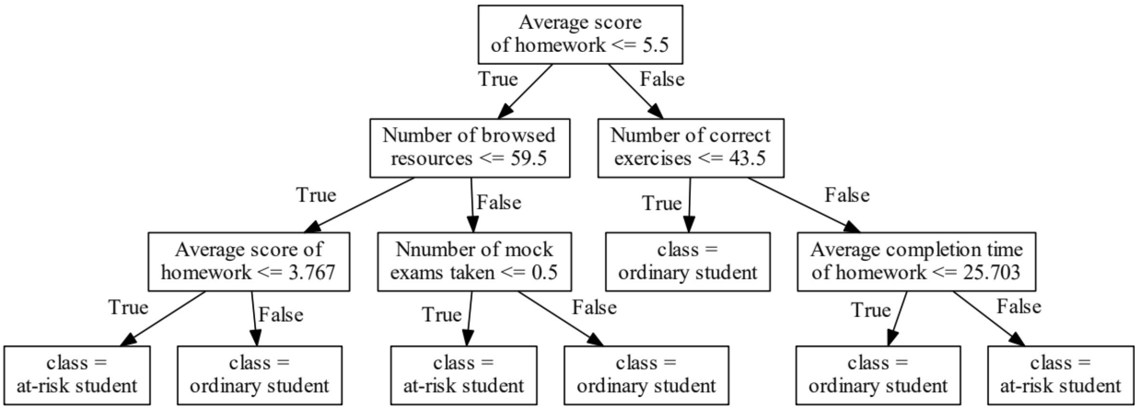

Fig. 13. Decision tree classification results.

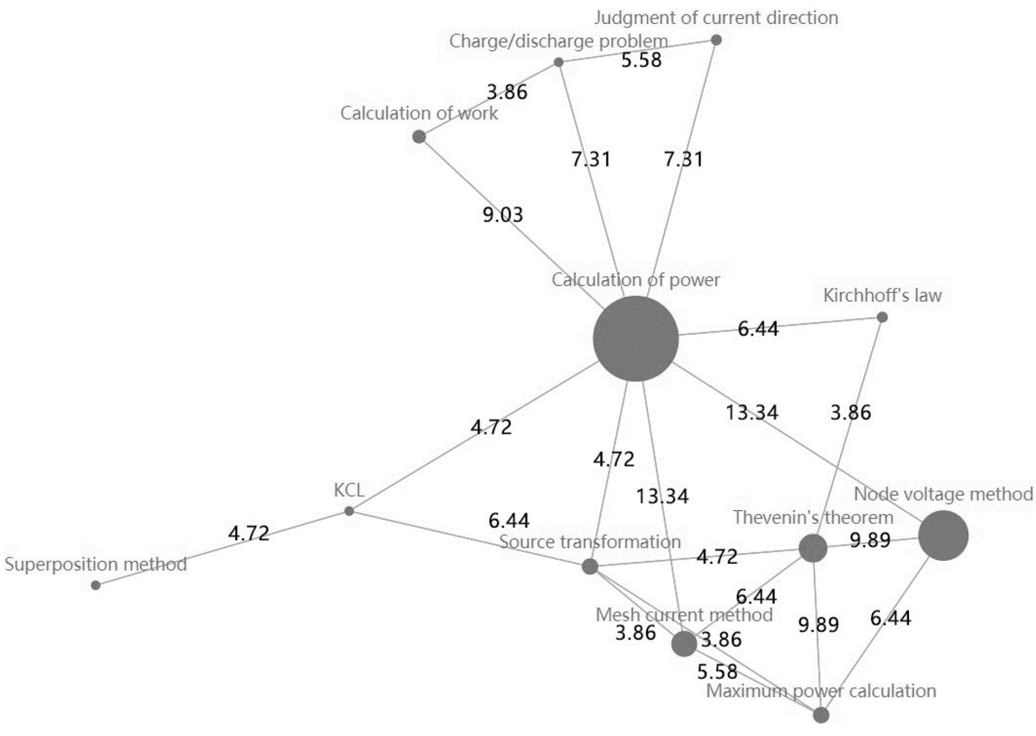

Fig. 14. Correlation analysis results.

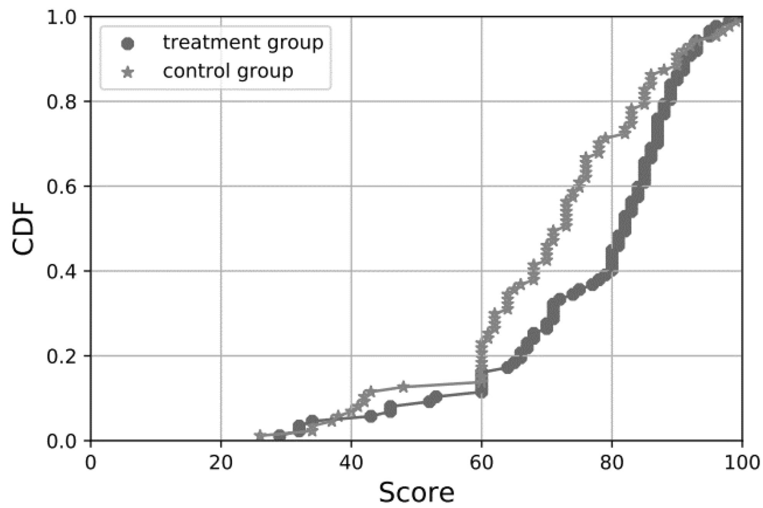

Fig. 15. CDF comparison of the students' scores.

tigated simultaneously within the same exercise. Only students with the ability to solve all of these knowledge points can complete the exercise correctly.

It can be seen from Fig. 14 that the point representing power calculation is the largest, followed by the node voltage method, Thevenin's theorem, and the mesh current method, indicating that these knowledge points are the most frequently investigated. From the point of view of a single knowledge point, the power calculation is the most frequently examined, with almost half of the exercises consisting of this knowledge point. The number of connections between the power calculation knowledge point and other knowledge points is also the largest, indicating that this knowledge point is often examined together with other knowledge points, which is extremely important. At the same time, there are weights between the points, and the value of the weights indicates the support degree of the two knowledge points. The greater the weight, the more frequently the two knowledge points appear together in the same exercise. With the correlation analysis, teachers and students can have a clearer understanding of the importance and correlation of the knowledge points, so that they can grasp the key points and improve efficiency.

5.3 Comparison of the Scores between Treatment and Control Groups

5.3.1 The CDF comparison of students' scores

We selected the 89 students who used this platform as the treatment group, while the other 89 students who did not use the platform comprised the control group. The average final exam score in the treatment group was 76.8, which was 6.3 points higher than the control group's 70.5 score. The CDF comparison chart of students' scores between the two groups is shown in Fig. 15. As can be seen from Fig. 15, overall, the students who used the platform outperformed those in the control group, indicating that using this platform can effectively improve students' performance. In addition, it can be seen from Fig. 15 that the influence of this teaching method on middle-level students is greater than that on high-scoring and low-scoring students.

5.3.2 Descriptive Statistics

Descriptive statistics are given in Table 2. The students in the treatment group and the control group were divided into three categories according to their grades, namely at-risk students, average students and excellent students, as shown in Table 2. After that, the average score and standard devia-

Table 2. Descriptive statistics

	Treatment Group			**Control Group**			**Average Scores Difference**
Group	**Sample Size**	**Average Score**	**Standard Deviation**	**Sample Size**	**Average Score**	**Standard Deviation**	
At-risk Students	29	58.41	13.25	29	52.66	11.54	5.75
Average Students	30	81.73	3.03	30	71.8	3.55	9.93
Excellent Students	30	90.57	3.59	30	87.57	6.11	3
All Students	89	76.8	15.75	89	70.49	16.16	6.31

Table 3. Results of Independent Sample T-test of Treatment Group and Control Group

Category	t-value	p-value	Note
At-risk Students	1.734	0.088	
Average Students	11.451	0.000	$p < 0.01$**
Excellent Students	2.200	0.032	$p < 0.05$*
All Students	2.593	0.010	$p < 0.05$*

* Represents that a difference exists at the significance level of 0.05.
** Represents that a difference exists at the significance level of 0.01.

tion of each category were calculated respectively, and then the descriptive statistical data of two groups were compared. As can be seen from Table 2, students of each category in the two groups have significant differences in scores. Furthermore, the score difference of the average students is greater than the other two categories, which implies that the intelligent education prototype is especially suitable for the average students, followed by the at-risk students.

5.3.3 Independent Sample T-test

To validate the educational prototype's effectiveness, an independent sample t-test was conducted between the scores of the treatment group and the control group. The results in Table 3 show that the score difference of all students is significant. Moreover, the score differences for average students and excellent students are also significant. Furthermore, the score difference of average students is greater than that of excellent students, which implies that the proposed educational prototype is especially suitable for average students.

5.4 Discussion

The education prototype proposed in this paper can effectively collect behavioral data of students in the learning process. With these data, on the one hand, we can make statistical analysis to show the learning situation of students, on the other hand, we can carry out more in-depth mining analysis. With cluster analysis and classification analysis, we can help teachers find students in need of help in time, so as to help improve these students' performance. With correlation analysis, we can analyze the importance and relevance of knowledge points, so as to assist teachers and students grasp the key points to improve efficiency. Finally, we compare students' final exam scores to verify the validity of this education prototype. On the one hand, the statistical analysis and CDF chart were given to make a simple score comparison. On the other hand, in order to further verify the score difference between the treatment group and the control group, an independent sample t-test was conducted. The results fully prove that this education prototype can indeed significantly improve students' achievement. In addition, according to the results of this experiment, teaching based on this educational model has a greater impact on average students.

Of course, there are some shortcomings in the experimental part of this paper. For example, the learning ability of students in the treatment group and the control group cannot be guaranteed to be consistent, so that there are some deficiencies in the control variables. In addition, we do not have some phased tests to record students' academic performance at each stage for a more detailed analysis. Finally, because the control group students adopt offline education, a lot of behavioral data cannot be collected, which limits some data analysis.

6. Conclusion

In this paper, we introduced the design and implementation of the intelligent education prototype for an electronic systems course. Our prototype can collect students' data to closely monitor users' progress and performance in order to personalize education and alert teachers to at-risk students. The goal of this intelligent education prototype is to improve students' learning efficiency and performance. An experiment was conducted to verify the teaching method's performance. The participants were 178 students from a joint QM–BUPT program. The results of the experiment prove that there was a significant change in the scores of the students who used the intelligent education prototype. Based on the above research results, this study proposes that it is appropriate to use a personalized teaching method based on this intelligent education prototype. However, our experiment is limited in scope. In the future, we hope to conduct similar experiments in more classes that cover a diverse student body in order to test the usability of our intelligent education prototype and make further improvements.

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