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The Innovation of Online Social Science Education Facilitated by Data Mining

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Social sciences are a valuable area of study in universities. In this paper, a brief description is given of the traditional teaching mode and of the algorithm for a personalized learning path planning used on the online platform in the online education mode. For the study, data was collected from a sample of students enrolled in social science classes in 2019 and 2020 at the Northeast Agricultural University. The students were divided into control classes and experimental classes. The control classes were instructed using the traditional teaching mode, while the experimental classes received online teaching in addition to the traditional teaching mode. The students were tested before the beginning of the experiment and then again after one month of being taught via the traditional mode (control group) and the blended learning mode (experimental group). A questionnaire survey was conducted among students in the experimental classes. The scores obtained by students using the traditional online platform were compared with those of students who learned via the online platform that included the learning path planning algorithm. The results showed that the online platform with the learning path planning delivered more accurate and appropriate learning paths more consistently although students were at different learning levels. The social science test scores of the control classes that adopted the traditional teaching mode did not change significantly before and after the one-month teaching period, while most of the test scores of students in the experimental classes that adopted online teaching achieved scores ranging between 81 and 100 after the set teaching period. The survey results showed that the blended teaching mode could meet students' learning needs more satisfactorily, and most students used the online platform for the purpose of consolidating their knowledge.

Keywords: data mining, social science, online platform, knowledge concept interaction degree

1. INTRODUCTION

The cultivation of talents is crucial for the development of a country. Higher education institutions provide the learning environment and courses conducive to the cultivation of talents, which has become increasingly important in the 21st century (Shukor et al., 2015). When cultivating talents, higher education institutions need to ensure that students have a sound knowledge of the social sciences (Maté et al., 2016). Most of the students who attend higher education institutions are young people. Their three fundamental values have not yet fully developed, but the amount of information available to them, especially information about society, has greatly increased. Not all of the information is trustworthy and reliable, and various types of information have different effects on people's three fundamental values. Once the information produces an adverse effect on college students' minds, the adverse effects on students' future are unpredictable, and it may even cause harm to the construction of the country. Therefore, the first and foremost task of higher education institutions in educating and guiding college students is helping them to establish the correct world views through social science courses (Wu et al., 2020). The traditional way of teaching social science subjects involves classroom teaching, after-school homework or activities related to the conventional curriculum (Kokkodis et al., 2015). However, nowadays, technological developments and the improvement of people's living standards have brought about changes in the behaviors and expectations of college students,

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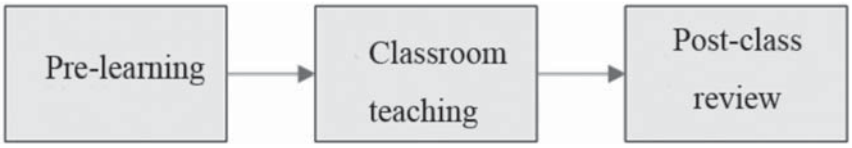

Figure 1 The traditional teaching mode.

so that today's students are becoming distinctly different from those in the past. Social science-based education for college students needs to change and combine with the modern Internet to enhance the learning effect. Su (2019) proposed an optimization method for online education data mining based on big data evaluation technology and found through experiments that the method could improve the mining accuracy, reduce the mining error rate and ensure the stability of data mining. Li et al. (2021) designed a cross-dimensional online education opinion data mining model based on fuzzy association rules and found through simulation that the model had the advantages of wide scope, high speed and high accuracy, which can provide data support for educational reform. Bozkir et al. (2015) used two data mining methods, the decision tree algorithm and the clustering algorithm, to explore the relationship between science and mathematics in terms of multi-causal single effect and multi-causal multiple effects. The results showed that students' academic outcomes in science or mathematics were influenced not only by course-specific variables but also by other related variables.

2. TRADITIONAL EDUCATION MODE

The main purpose of offering social science courses to students in higher education institutions is to provide correct guidance regarding their worldview, outlook on life and sense of values. For the purpose of guidance, the relevant knowledge is usually interpreted and taught by means of examples. This teaching mode is similar to the conventional knowledge teaching mode, and the traditional one is usually adopted when teaching social science subjects (Wang, 2021).

As shown in Figure 1, the first step is pre-learning. The teacher will establish the scope of pre-learning for students according to the predetermined teaching plan and progress before the formal teaching, and ask students to prepare for lessons before class. In this stage, the teacher will not have additional requirements, and the pre-learning materials are textbooks for social science-based education (Martín-García et al., 2019). This is followed by classroom teaching, which is the major component of the traditional teaching mode. The teacher will explain the assignments assigned in the previous class, focusing on the parts where students frequently make mistakes. This classroom teaching is teacher-centred and the students accept the imparted information passively. The teacher plays an active role in the classroom and interacts with students only when asking them questions. Finally, there is the post-class review. Generally, the teacher assigns relevant post-class assignments that require students to review the information given to them in class and consolidate their knowledge. The teacher also establishes the scope of pre-learning for the next class. The items used as post-class assignments in the social science-based teaching mode are not always written assignments, but may also be practical activities to help students establish the three fundamentals values (Tu, 2018).

In the traditional teaching mode, the teacher is the main player in the classroom and, apart from textbooks, is the main source of information. The advantage of this mode is that it is easy to manage. In this mode, students are regarded as a whole, and the teacher can deal with the mistakes made by individuals in a uniform manner and remind students who have not made mistakes not to make the same mistakes. However, the shortcomings of the traditional teaching mode (Liu et al., 2017) are: (1) the teaching mode is single, and students are not highly motivated; (2) the mode is rigid and not conducive to encouraging students' enthusiasm for learning; (3) after-school hours are not used efficiently for learning.

3. ONLINE EDUCATION MODE BASED ON DATA MINING

3.1 Learning Route Planning Method Based on Feature Mining of Students' Knowledge Point

When using the online platform for learning, students can freely choose learning resources, and the online platform will record the learning behavior data (Blockeel, 2015). Through the regular mining of the recorded learning behavior data, the online learning path is planned in a personalized way. In this paper, the knowledge points provided by the online platform are used as nodes to build a complex network, and then a directed learning path network is constructed based on the temporal data of students' learning behaviors on the online learning platform (Jialun et al., 2021). Then, the KL scatter matrix and matrix feature vector are used to divide the network to obtain the network classes of knowledge nodes corresponding to different learning difficulties. The optimal learning path is selected as the learning path for students to learn the knowledge points under that category of difficulty (Mobasher et al., 2017).

The personalized planning of learning paths based on data mining of knowledge points and characteristics of students' learning behaviors is shown in Figure 2. The steps are as follows.

① Firstly, the time series data D of students' behavior at learning different knowledge points of the social science-based course on the online platform is collected.

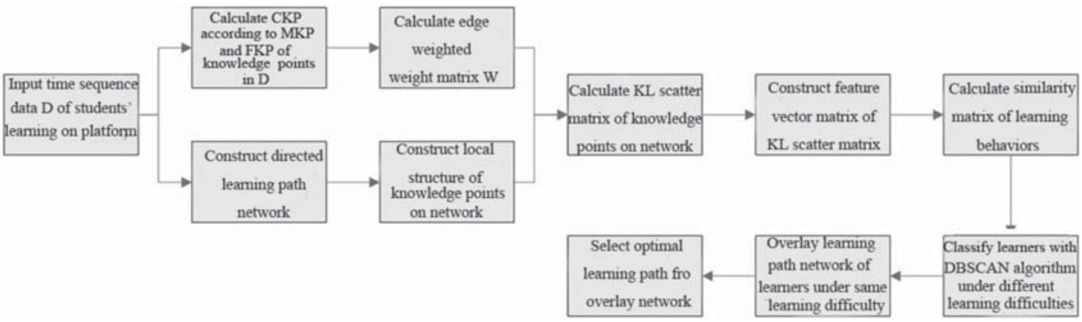

Figure 2 Learning path planning method based on students' knowledge points and learning behaviors.

② The conceptual interaction achievement of every knowledge point in D is calculated using the following calculation formula:

$$\begin{cases} ckp_i = \frac{mkp_i}{fkp_i} \\ CKP = \{ckp_i | i = 1, 2, 3 \cdots m\} \\ MKP = \{mkp_i | i = 1, 2, 3 \cdots m\} \\ FKP = \{fkp_i | i = 1, 2, 3 \cdots m\} \end{cases}, \quad (1)$$

where ckp_i is the student's conceptual interaction achievement of the i-th knowledge point in the social science based education course, mkp_i is the student's mastery level of the i-th knowledge point in the social science based education course, which comes from the knowledge test results of students on the platform, fkp_i is the relative difficulty coefficient of the i-th knowledge point in the social science based education course, CKP, MKP and FKP are the set of ckp_i, mkp_i and fkp_i, and m is the number of knowledge points in the course.

③ A directed weighted learning path network of students' knowledge points in the social science-based education course is constructed according to D. The construction formula is:

$$\begin{cases} DLPN = G(M, CKP, E, W) \\ M = \{1, 2, 3, \cdots, m\} \\ CKP = \{ckp_i | i = 1, 2, 3, \cdots, m\} \\ E = \{e_i | i = 1, 2, 3, \cdots, p\} \\ W = [w_{ij}]_{m \times m} \\ w_{ij} \frac{ckp_i}{ckp_j} \end{cases}, \quad (2)$$

Where $DLPN$ is a directed weighted learning path network, M is the set of nodes in the network, i.e., the set of knowledge points in the social science based education course, E is the set of connection edges between knowledge points in the network (the number of connection edges is P), W is the set of weights of connection edges between knowledge points, and w_{ij} is the edge weights from knowledge point i to knowledge point j.

④ After constructing the $DLPN$ of every student according to the above steps, the KL scatter values of knowledge point in-degree and out-degree in every $DLPN$ are calculated. Then, the local structural similarity of nodes in $DLPN$ is calculated, so as to construct the KL scatter matrix of the $DLPN$. The corresponding calculation formula is:

$$\begin{cases} KL_{DLPN} = [kl_{ij}]_{m \times m} \\ kl_{ij} = H_{KL}(P_{ID}(i)|P_{ID}(j)) + H_{KL}(P_{OD}(i)| \\ P_{OD}(j))H_{KL}(P_{ID}(i)|P_{ID}(j)) \\ = \begin{cases} \sum_{k=1}^{l_{ID}} \left(P_{ID}(i,k) \ln \frac{p_{ID}(i,k)}{p_{ID}(j,k)} \right) & p_{ID}(j,k) \neq 0 \\ 0 & else \end{cases} \\ l_{ID} = \min(l_{ID}^{IDKN}(i),\ l_{ID}^{IDKN}(j)) \\ H_{KL}(P_{OD}(i)|P_{OD}(j)) \\ = \begin{cases} \sum_{k=1}^{l_{OD}} \left(p_{OD}(i,k) \ln \frac{p_{OD}(i,k)}{p_{OD}(j,k)} \right) & p_{OD}(j,k) \neq 0 \\ 0 & else \end{cases} \\ l_{OD} = \min(l_{OD}^{OKDN}(i),\ l_{OD}^{ODKN}(j)) \end{cases}, \quad (3)$$

Where KL_{DLPN} is the KL scatter matrix of $DLPN$, kl_{ij} is the KL scatter of the connected node i and node j in $DLPN$, $H_{KL}(P_{ID}(i)|P_{ID}(j))$ is the KL scatter of the in-degree of the connected node i and node j in $DLPN$, $H_{KL}(P_{OD}(i)|P_{OD}(j))$ is the KL scatter of the out-degree of the connected node i and node j in $DLPN$, and $p_{ID}(i,k)$, $p_{OD}(i,k)$ is the in-degree and out-degree probabilities of node i and node j in $DLPN$.

⑤ The feature values of the matrix and the feature vectors of the feature values are obtained according to KL_{DLPN}. Then, the corresponding feature vectors of the feature values ranked in the top three in descending sort (Gao et al., 2021) are selected to construct a feature vector matrix, $V_{3 \times m}$.

⑥ After obtaining the feature vector matrix $V_{3 \times m}$ for the KL_{DLPN} of every students, the $V_{3 \times m}$s of students are compared to obtain their learning behavior similarity matrices. The calculation formula is:

$$\begin{cases} S = [S_{IJ}]_{N \times N} \\ S_{IJ} = [S_{IJ}(\omega_i,\ \omega_j)]_{3 \times 3} \\ S_{IJ}(\omega_1,\ \omega_j) = dis(\omega_i,\ \omega_j) \cdot \cos(\omega_i,\ \omega_j) \\ = \sqrt{\sum_{j=1}^{n} |\omega_i - \omega_j|^2} \times \frac{\sum_{j=1}^{n} \omega_i \cdot \omega_j}{\sqrt{\sum_{j=1}^{n} \omega_i^2} \sqrt{\sum_{j=1}^{n} \omega_j^2}} \end{cases}, \quad (4)$$

where S is the similarity matrix of the KL scatter matrix representing the learning behaviors of the N students learning social science on the online platform, S_{IJ} is the matrix determinant value of the similarity between the I-th students and the J-th students among N students, and $S_{IJ}(\omega_i, \omega_j)$, $dis(\omega_i, \omega_j)$ and $\cos(\omega_i, \omega_j)$ are the similarity, Euclidean norm and cosine similarity of row vector ω_i in $V_{3\times m}(I)$ and row vector ω_j in $V_{3\times m}(J)$.

⑦ KL_{DLPN} and S obtained from the above steps are used as input data, and the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (Chen et al., 2021) was used to classify learners according to primary, intermediate and advanced interaction achievements of the knowledge points, i.e., the ultimate goal that students want to achieve after they receive social science-based education.

⑧ The directed weighted learning path overlay network of the mastery level of the social science based education knowledge point is obtained by performing adjacency matrix superposition on the $DLPN$ of students who are one type of learner. Then, the path with the highest knowledge point conceptual interaction achievement is selected from this overlay network as the optimal personalized learning path for this type of learner (Yang, 2021).

4. SAMPLE ANALYSIS

4.1 Experimental Subjects

In this study, the sample comprised students from classes in 2019 and 2020 at the Northeastern Agricultural University. There were 200 students in every class, with an equal number of males and females. The students in every class were randomly and equally divided into a control group and an experimental group, with an equal number of males and females in each group. The teachers of the social science subjects had more than five years of teaching experience. In addition to being familiar with the traditional teaching mode, they were also flexible enough to apply the online teaching platform.

4.2 Experimental Methods

4.2.1 Effectiveness of Learning Path Planning Algorithms in Online Platforms

Before comparing the scores of the two groups of students (control group and experimental group) to determine the effectiveness of the traditional mode of teaching and the blended teaching approach, the recommendation performance of the online platform that included the learning path planning algorithm was tested. After a student achieved a knowledge point using the online platform, the platform would recommend the knowledge points to be learned subsequently, thus guiding the student to plan the learning path to the next knowledge point. The traditional online platform recommended knowledge points to students randomly within the corresponding range of knowledge points, while the online platform made personalized learning paths according to students' learning behaviors and recommended the next knowledge points.

In this test, a total of 50 knowledge points in the social science course was selected from the online platform, and 10 teachers with five years of teaching experience planned learning paths for 50 knowledge points according to primary, intermediate and advanced levels. Then, the traditional online platform and the online platform which included the learning path planning algorithm were used to provide the learning paths of knowledge points of the social science course for students at the three learning levels, and the accuracy of the learning paths planned by the online platform was obtained by comparing them with the standard learning paths.

4.2.2 Practical Testing of Students

First, students in every class were divided equally into a control class and an experimental class. The control classes were taught social science via the traditional teaching, while the experimental classes also used the online platform in addition to the traditional teaching mode.

The traditional teaching mode Followed these steps. ④ Ordinary classroom teaching: teachers taught the social science course to students according to the teaching schedule and explained the difficult points and knowledge points in the textbook. ⑤ Teachers assigned reading materials and accompanying homework after class and explained the difficult points in the homework in class.

In addition to the traditional teaching mode mentioned above, the experimental classes adopted the online teaching mode to support their learning. In this study, the online platform used by the teachers of the experimental classes was constructed by the institution. The relevant teaching materials were mainly educational videos recorded by the teachers according to the teaching plan and the corresponding knowledge points. Every video contained a knowledge point relevant to the social science course and was about 10 minutes long. Every video was accompanied by corresponding test questions. When students used the online platform, the platform collected the students' knowledge learning time sequence and mine the learning behavior of all the students in the experimental classes according to the learning path planning algorithm described above, so as to provide personalized learning paths for students with different mastery of social science knowledge points, i.e., recommend appropriate knowledge point videos to students on the platform.

4.3 Testing Teacher Effectiveness

In order to test the effectiveness of online platform education, both control classes and experimental classes were given a social science pre-test, scored out of 100. Then the control classes were taught in the traditional mode, while the experimental classes were taught via the online platform in addition to the traditional teaching mode. After one month, the students in the control and experimental classes were tested again.

In addition, a questionnaire survey [15] was conducted among the students in the experimental classes, which was

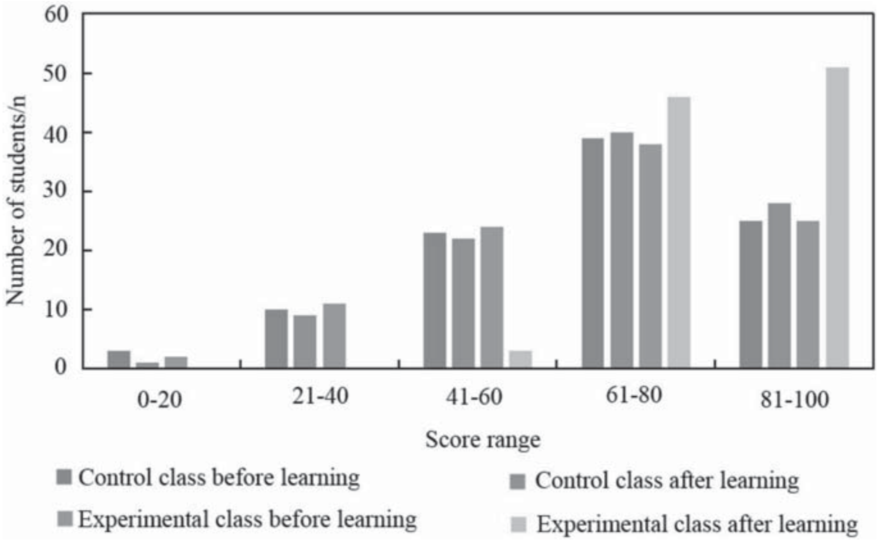

Figure 3 Accuracy of learning paths provided by two online platforms for students at different learning levels.

anonymous and included the following questions. ④ What is your main motivation for using the online platform to learn: teacher's requirement, consolidating knowledge, or interest? ② What form of learning do you prefer in the combination of online platform and traditional teaching mode: traditional classroom, online platform, or both? ④ How is your communication with others in the mixed teaching mode: more active online, more active offline, or both? ④ Do you think the mixed teaching mode can meet students' learning needs? ⑤ Which part of the mixed teaching mode are you more satisfied with: traditional classroom, online platform, or both?

4.4 Experimental Results

The traditional online platform recommended knowledge points for students randomly, while the online platform that included the learning path planning algorithm developed personalized learning paths according to students' learning behaviors and learning levels. Figure 3 shows the accuracy of the learning path planning provided by the two platforms for students at three learning levels. For students at the primary level, the accuracy of the knowledge point learning paths given by the traditional online platform was 83.2% compared to the standard paths, and the accuracy of the knowledge point learning paths given by the platform with the path planning algorithm was 98.4%. For students at the intermediate level, the accuracy of the knowledge paths given by the traditional online platform was 75.6%, and the accuracy of the knowledge paths given by the platform with the path planning algorithm was 98.4%. For students with advanced learning level, the accuracy rate of knowledge point paths given by the traditional online platform was 70.1%, and the accuracy rate of knowledge point paths given by the online platform with path planning algorithm was 98.3%.

As shown in Figure 3, the accuracy rate of the knowledge point paths given by the traditional online platform gradually decreased as students' learning levels increased. The increase in students' level meant that the number of knowledge points increased and the requirement for mastery increased, which made the knowledge point path planning more complicated. The traditional platform gave knowledge point recommendations randomly within a specific range without considering whether students have completely mastered it, which eventually made the planned knowledge point paths deviate from the optimal paths. Before producing personalized learning paths, the platform with the path planning algorithm determined students' learning level based on their learning behaviors; hence, the obtained paths were closer to the standard optimal paths.

The test results of the experimental and control classes before and after learning are shown in Figures 4 and 5. Figure 4 shows the social science course scores of students in the 2019 control class and the experimental class before and after learning. Figure 5 shows the scores students in the 2020 control class and the experimental class before and after the one-month period of learning. Both Figures 4 and 5 show that there was no significant change in the scores of the control class before and after learning, with students in the 2019 control class scoring between 61 and 80 points, and students in the 2020 control class scoring between 41 and 80 points. The scores of students in the experimental classes showed a significant increase, scoring between 61and 80 points in the post-teaching test.

The results of a simple questionnaire survey of the students in the experimental classes after one month of learning via the blended learning mode are shown in Table 1. The results of the questionnaire survey showed that most students were motivated to use the online platform in the new mode to consolidate their knowledge, the second motivation was teachers' requirements, and the third motivation was their interest in the online format; most students preferred the combination of traditional classroom and online teaching in the new mode, and only a very small number of students favored online teaching, believing that traditional classroom teaching was not needed; the anonymity of the Internet in the new mode put students and teachers on a more equal footing when discussing issues and made students more open to discussion, so the number of those who were more active

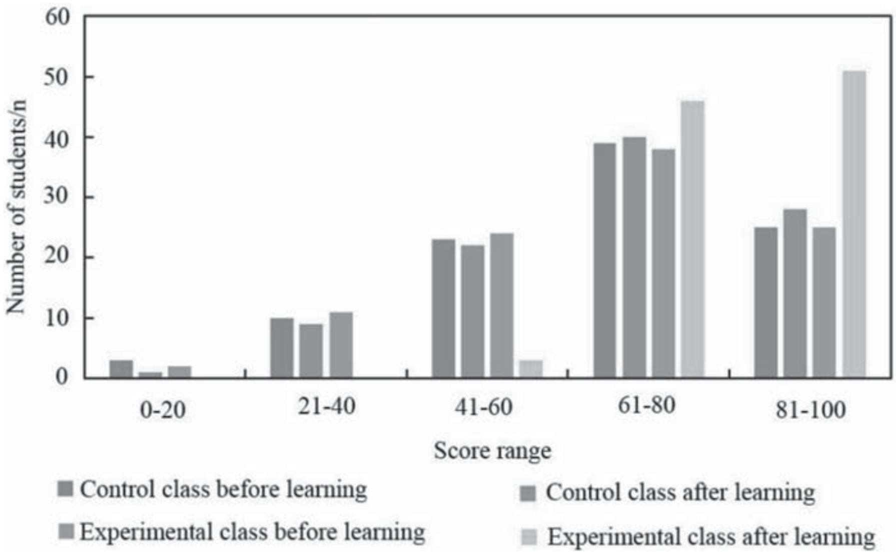

Figure 4 Scores of social science course students in the 2019 class in the control group and the experimental group before and after learning.

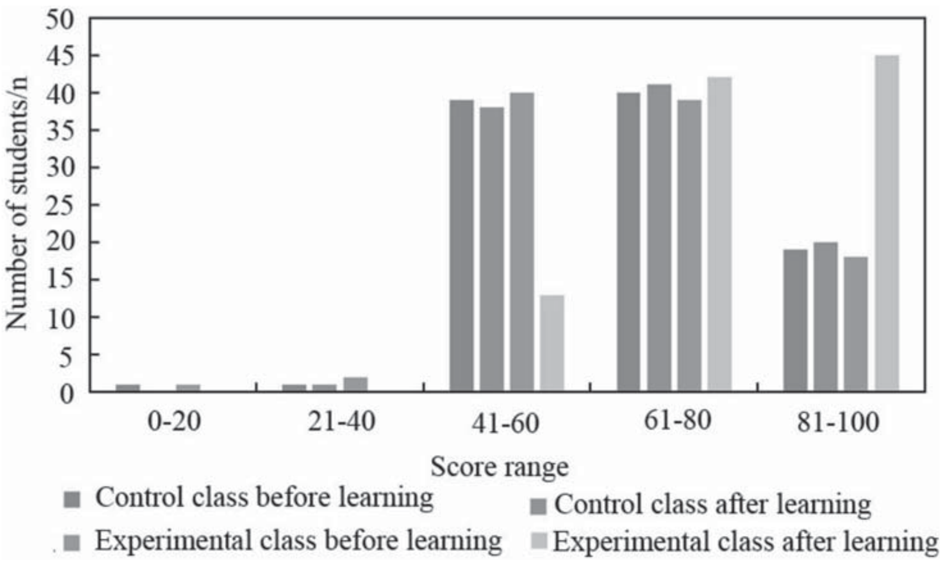

Figure 5 Scores of social science course students in the 2020 class in the control group and the experimental group before and after learning.

Table 1 Questionnaire results.

Question number	Options	Percentage
①	Teachers' requirements	30.2
	Consolidate knowledge	48.3
	Interest	21.5
②	Traditional classroom	33.2
	Online platform	7.7
	Traditional classroom + online platform	59.1
③	More active online	55.3
	More active offline	7.2
	Active both online and offline	37.5
④	Traditional classroom meets demands better	31.9
	Online platform meets demands better	9.8
	Traditional classroom + online platform meets demands better	58.3
⑤	Traditional classroom is more satisfying	29.2
	Online platform is more satisfying	11.2
	Traditional classroom + online platform is more satisfying	59.6

online was higher. Most students thought that the combination of traditional classroom and online teaching in the new mode could better meet students' learning needs. Only a small number of students thought that online teaching alone could meet learning needs. Most students were more satisfied with the combination of traditional classroom and online in the new mode, while few students were more satisfied with the single online platform. Overall, the results of the questionnaire survey showed that students in the experimental classes preferred the blended learning approach which combined traditional and online teaching mode. Most of the students used the online platform for the purpose of consolidating knowledge, the online communication and discussion were more active, and most of them thought that the combination of traditional teaching and online platform complemented each other to better meet their learning needs and were satisfied with the blended teaching/learning approach.

5. CONCLUSION

In this paper, a brief description of the traditional mode of teaching and learning was given. An algorithm was proposed for personalized learning path planning on the online platform in the online education mode, and a study was conducted with students from the 2019 and 2020 classes at the Northeast Agricultural University. The students were divided into control classes and experimental classes. The control groups were taught by the traditional mode, while the experimental groups used the online platform in addition to the traditional mode. The experiment was conducted over one month. Finally, students in the experimental classes were investigated through questionnaires. A comparison was made between the traditional online platform and the online platform that included the learning path planning algorithm. The results are as follows. (1) The online platform with the learning path planning algorithm not only gives more accurate learning paths, but is also more stable for students at different learning levels. (2) Figures 2 and 3 showed that the scores of social science students in the control classes did not change much as a result of the traditional teaching method, while the scores of students in the experimental classes changed significantly, increasing to between 81 and 100 points. (3) The questionnaire survey conducted with the experimental classes showed that most students in these classes thought that the combination of online platform and classroom teaching was satisfactory because they complemented each other and could better meet their learning needs; most students preferred the combined form of learning, used the online platform for the purpose of consolidating their knowledge, and were more active online.

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