Design of Personal Learning Model Recognition Model for Online Teaching of Ideological and Political Theory Course

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Abstract. Accurate identification of students' learning modes in online teaching of ideological and political theory courses is helpful to improve students' concentration in the learning process and enhance the effect of online teaching of ideological and political theory courses. To this end, this paper designed a personal learning pattern recognition model, set the identification criteria for the matching rules of personal learning pattern type and behavior purpose, collected students' learning data according to the teaching video browsing situation, and analyzed their learning behavior trajectory and the degree of attention in the learning process. By comparing the analysis results with the preset identification criteria, the quantitative identification results of online learning modes of ideological and political courses are obtained. The experimental study shows that the recognition results of the model in this paper are close to the actual online learning types of students in ideological and political courses, and after the application of this model, the test scores of students in ideological and political courses have been significantly improved, which proves that this model has a high promotion value.

Keywords: Ideological and political theory course · Online teaching · Personal learning mode · Pattern recognition model

1 Introduction

Ideological and political theory courses aim at guiding students to set up correct outlook on life, values, world outlook, cultural outlook and moral outlook, focusing on guiding students to set up correct learning goals in life, and it is also one of the key courses to carry out the fundamental task of cultivating people through virtue. Through the study of ideological and political theories, students can closely combine the development of their own quality with the process of the country and society, and make students understand that study is not only for exams, but also for improving their own quality and broadening their horizons, so as to discover their significance to the society and try their best to realize their own value. It can be said that the course of ideological and political theory is a very practical course of social significance. However, it is not difficult to see from the classroom teaching of traditional ideological and political theory course that many students are not interested in this course, or even tired of it. The main reason lies in

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that most teachers mainly teach theory, the teaching form is monotonous, the content is single, resulting in students' lack of interest, the teaching quality is low [1].

In order to truly and effectively realize the value of ideological and political theory course, we should change the traditional teaching method and design the online teaching mode in combination with the background of "Internet+" in the new era. Online teaching mode can break the limitation of course teaching in time and space and provide a more scientific and convenient platform for students to learn.

Individual learning behavior is the social behavior in the classroom context and the external embodiment of classroom concentration. Students' classroom behavior reflects students' learning state and learning efficiency and is closely related to the quality of classroom teaching. Online learning behavior is based on the concept derived from online learning, which is the learning behavior occurring in the network environment. Through the identification of the personal learning mode of the online teaching of ideological and political theory courses, the basic learning rules of students can be summed up, so as to adjust the wrong learning methods and learning modes.

At present, there are some research results about learning pattern at home and abroad, including learning pattern recognition method based on network teaching platform, learning pattern recognition method based on random forest and learning pattern recognition method based on data mining. However, the traditional recognition methods have the problem of insufficient recognition accuracy, which is difficult to provide reference value analysis data for students' Ideological and political theory course learning, resulting in its poor application. In order to solve the shortcomings of traditional recognition methods, this study comprehensively analyzes students' web browsing behavior and online video learning behavior, and realizes the optimization design of personal learning pattern recognition model for online teaching of Ideological and political theory course, so as to improve the recognition accuracy and application value of the model.

2 Personal Learning Pattern Recognition Model Design

Personal learning pattern recognition model collects data about online learning behavior and learning style, and uses correlation analysis to explore the relationship between learners' learning style and online learning behavior. Then the decision tree algorithm is used to build the learning style prediction model, and all online learning behavior features are added to the training process [2]. After pruning the decision tree model, the prediction model of learning style of each dimension is obtained. Through four learning style prediction models, learners' learning patterns can be automatically identified by analyzing learners' online learning behavior data. The specific identification process is shown in Fig. 1.

In the process of personal learning pattern recognition designed in this paper, the basic recognition process in Fig. 1 is used to make a specific analysis of students' classroom behavior and network browsing behavior in the learning process, so as to ensure the accuracy of the final recognition results. Among them, classroom performance behavior mainly refers to the degree of activity and concentration of students in online class. It mainly uses the camera equipment on the remote computer to collect the video information of students' learning. On this basis, combined with the video image processing and

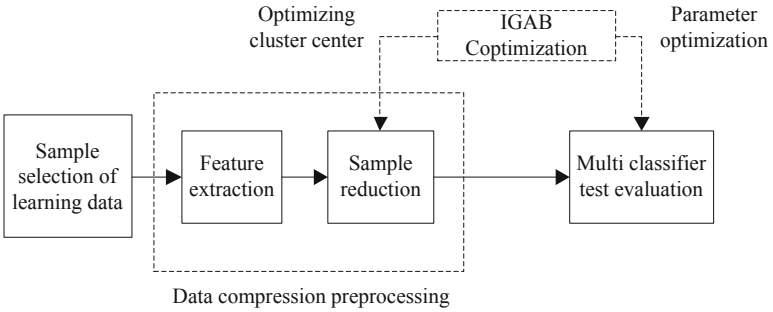

Fig. 1. Flow chart of personal learning pattern recognition

analysis technology, the learning behavior recognition results of students' classroom performance are obtained. The browsing behavior of students is mainly the browsing data of students, including browsing behavior data, searching behavior data, downloading behavior data and so on. Based on the above two parts, a comprehensive identification result of personal learning mode in online teaching of ideological and political theory courses is obtained.

2.1 Matching of Personal Learning Model Types and Behavior Items

In order to make the research results universal, this study only uses the behavior items of the most commonly used function modules in the learning management system to predict the learning style. Common function modules include discussion area, homework and online test. On the basis of literature review and platform data analysis, the dimensions of e-learning style model and behavior items are matched, which is used as the standard of personal learning pattern recognition in online teaching of Ideological and political theory course. Among them, behavioral items used to identify information processing dimensions include: number of posts, number of replies, number of posts read, number of posts read and time to submit homework, etc.

Active learners are better at using learning resources to assist in learning, and like to communicate with others. Use the discussion area in the learning platform to communicate with others through post, reply and other forms, and cooperate to complete tasks [3, 4]. Generally speaking, in the discussion area, active learners are more proactive in speaking and discussing than contemplative learners, and generally there are more posts and replies. Pensive learners like to solve problems on their own, and tend to think carefully before making decisions or taking actions. In contrast, dependent learners' learning attitude is not positive enough, they only complete the curriculum tasks required by the teacher, and rely on the teacher to give detailed and clear guidance. Therefore, dependent learners view more teacher posts, and pay less attention to other people's discussions or content that is not related to the task to be completed. After finishing the homework, dependent learners rarely check their homework for inspection and reflection. Due to the poor ability to complete tasks independently, it generally takes a long time to complete the homework. Independent learners are confident in their learning abilities and prefer to learn what they think is important. Compared with dependent learners, they are less

dependent on the teacher's guidance, pay more attention to themselves or what they are interested in, and complete their homework faster. In addition, combining the maintenance time and start time of the student's course concentration, as well as the student's browsing data, can get the student's learning habits, which can summarize the student's individual learning behavior law, and get the corresponding individual learning pattern recognition results.

2.2 Collect Online Personal Learning Behavior Data of Ideological and Political Courses

User browsing behavior acquisition is the process of extracting user browsing action information, and the captured information is the data source of the whole process of behavior analysis. The specific user behavior acquisition process can be shown in Fig. 2.

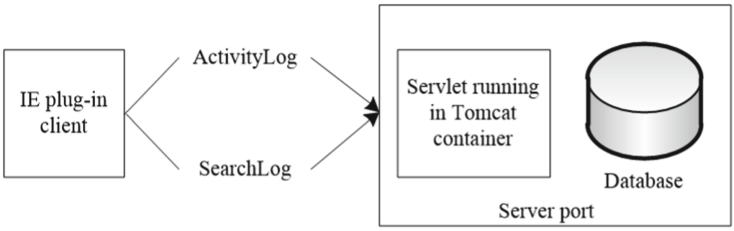

Fig. 2. Process diagram of user behavior acquisition

BHO technology is used to obtain the user's action information such as window events in the search process. The captured information includes action information and search web page information. This information can be uploaded to the server running in the container by the user in the form of logs. The process of users using search engines to find interesting information is a process of continuous interaction with search engines. Usually, the user enters a query keyword in the query box, and after analysis and processing inside the search engine, hundreds or even tens of thousands of related records are obtained. These records are sorted according to relevance to fix a number of records, usually one result. Page, presented to the user.

In each result page, each record usually contains the title, time, location identification, content summary and other information of the web page, representing the entrance of a web page. User interest information is obtained by combining four kinds of user browsing behaviors, such as page stay time, mouse click times, page access times and slider sliding times [5, 6]. Page dwell time belongs to window behavior, page access times belongs to repetition behavior, mouse click times and slider slide times belong to operation behavior. The user browsing behaviors collected by the browser plug-in are described in the form of basic behavior events and stored in the memory module of the recognition model.

The video data is recorded by the HD camera of the remote computer at the speed of 30 frames per second. The height of the camera is about the same as the eye height of the subject, about 25 cm away from the subject. Set the duration and interval of video data

acquisition, start the video data acquisition program immediately after the students start the video courseware in the online teaching platform, and close the acquisition program one minute after the video is closed. All the video acquisition results are stored in the recognition model in chronological order.

2.3 Personal Learning Behavior Video Data Preprocessing

Every picture in the video stream collected by the camera is a three channel RGB color image. Each pixel in the image is composed of R, G and B components, and the value possibility of each component is 255. Therefore, the original image contains a lot of information, and a pixel has 255 × 255 × 255 values. In order to reduce the amount of original image data and subsequent calculation, it is necessary to gray the image. In this study, the average value method is selected to carry out gray conversion for each pixel in the initial video image, and the gray processing results obtained can be expressed as:

$$GRAY = R = G = B = \frac{R(i.j) + G(i.j) + B(i.j)}{3} \tag{1}$$

To binarize a grayscale image, you need to set a threshold. All pixels in the image whose grayscale value is greater than or equal to the threshold are set to a grayscale value of 255, which represents the target object. On the contrary, set the gray value of pixels below the threshold to 0, which means the background or other areas [7–9]. The concrete realization of binarization is shown in formula 2:

$$f(x, y) = \begin{cases} 255, f(x, y) \geq \lambda \\ 0, f(x, y) < \lambda \end{cases} \tag{2}$$

Among them, (x, y) represents the coordinate value of a pixel, $f(x, y)$ represents the gray value of the coordinate point, and λ is the set threshold. On this basis, bilateral filtering is used to de noise the video image. Bilateral filtering is to segment the neighborhood according to the size of the pixel value of each point in the filtered image, then assign the relatively high weight to the category of the pixel value of the point, and then carry out the domain weighted sum to get the final bilateral filtering result. In the process of filtering, the mathematical expression to define the Gaussian function in the spatial domain is:

$$d(i, j, k, l) = \exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma_d^2}\right) \tag{3}$$

Then the mathematical expression of Gaussian kernel function of gray distance range is as follows:

$$r(i, j, k, l) = \exp\left(-\frac{\left|f(i, j)^2 - f(k, l)^2\right|}{2\sigma_r^2}\right) \tag{4}$$

Multiply the above formula 3 and formula 4 to obtain the weight function of bilateral filtering:

$$w(i, j, k, l) = \exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma_d^2} - \frac{\left|f(i, j)^2 - f(k, l)^2\right|}{2\sigma_r^2}\right) \tag{5}$$

The product of the weight w and the pixel f obtained by the above formula is added and divided by the sum of the weight w, and finally the pixel value $g(i, j)$ at the point (i, j) is obtained. The expression is shown in formula (6):

$$g(i,j) = \frac{\sigma \sum_{k,l} f(k,l) w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)} \tag{6}$$

In the above formulas, (i, j) and (k, l) are the output point and input point coordinates respectively, $\exp(*)$ represents the exponential function in mathematics, and the mathematical symbol σ represents the standard deviation of the space domain.

2.4 Extracting Behavior Features of Video Frame

When performing target detection on an image, the image contour is important to extract information. Contour detection is actually the process of hollowing out the pixels inside the closed edge lines of the image and retaining the closed contour shape. By traversing the contour points of the closed contour in turn, data such as coordinate points, contour area, and number of contours are obtained to infer the subject of the image The characteristics of the target. To determine the subject's behavior in classroom teaching videos, it is necessary to study the changes of the video frame images, mainly to detect and calculate the subject's motion amplitude in the frame images before and after the video, so as to infer the current learning behavior of students [10]. This process consists of two parts: first call the similar frame images of the two videos, make the difference between them, and get the difference binary image; then the difference binary image is obtained for the detection and area calculation of the connected domain, and the integrated video image The contour feature in, the feature extraction result of the subject's motion amplitude is obtained.

In addition to the above video features, according to the process of Fig. 3, select other feature indicators in the process of personal learning of online teaching of Ideological and political theory course, and carry out feature extraction according to the above process.

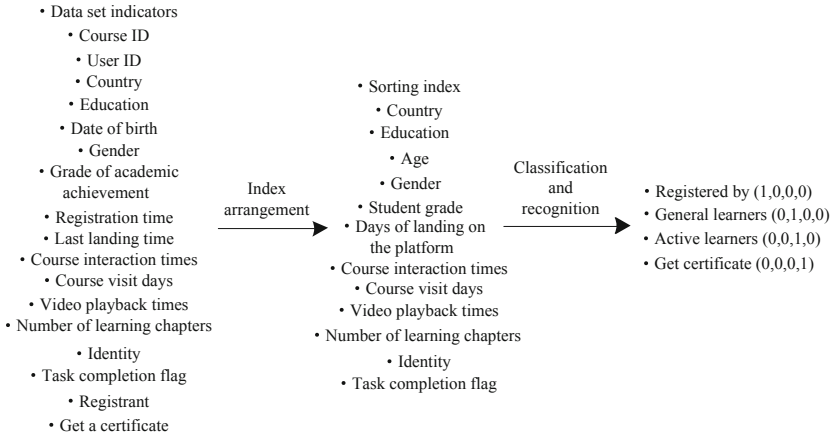

Fig. 3. Selection of individual learning characteristic indicators for online teaching

Finally, all the extracted learning behavior features are fused to obtain the final comprehensive feature extraction result.

2.5 Testing the Concentration of Online Teaching and Learning of Ideological and Political Theory Courses

According to the students' eye opening degree in class and the students' posture, expression, action and other characteristics in the classroom, the probability of students' class concentration is predicted. The judgment process of students' class concentration is shown in Fig. 4.

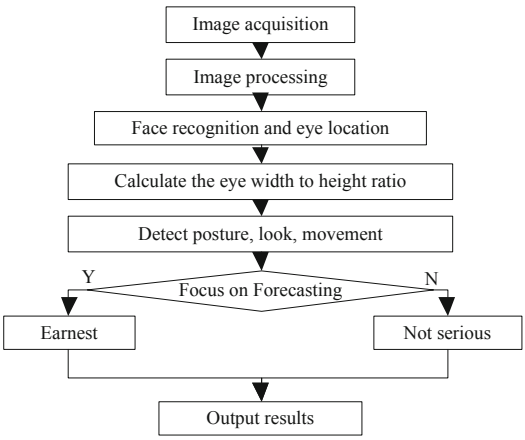

Fig. 4. Flow chart of individual learning concentration judgment

Pupil Location

Based on the collected and processed video image data, through coarse positioning of the given pupil contour, the horizontal and vertical coordinates x and y of each point on the pupil edge are obtained. Compare all the horizontal and vertical coordinates to obtain the minimum value of the horizontal coordinates. $x_{\min}$ and the maximum value $x_{\max}$, the minimum value $y_{\min}$ and the maximum value $y_{\max}$ of the ordinate, the minimum boundary rectangle of the pupil contour can be obtained through the range of the abscissa, the range of the abscissa of the rectangle is $(x_{\min}, x_{\max})$, and the range of the ordinate is $(y_{\min}, y_{\max})$. To obtain the area S of the smallest bounding rectangle, the calculation formula is as follows:

$$S = \sum_{y=y_{\min}}^{y=y_{\max}} \sum_{x=x_{\min}}^{x=x_{\max}} g(x, y) \tag{7}$$

The expression of the center of mass of the pupil contour is:

$$\begin{cases} X = \dfrac{1}{S} \displaystyle\sum_{y=y_{\min}}^{y=y_{\max}} \sum_{x=x_{\min}}^{x=x_{\max}} g(x,y) \times x \\ Y = \dfrac{1}{S} \displaystyle\sum_{y=y_{\min}}^{y=y_{\max}} \sum_{x=x_{\min}}^{x=x_{\max}} g(x,y) \times y \end{cases} \tag{8}$$

The precise position of the pupil center can be obtained by the centroid method, as shown in Fig. 5.

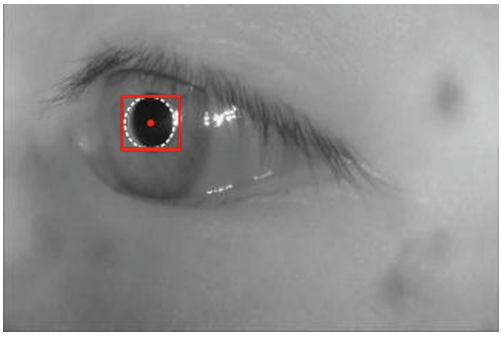

Fig. 5. Pupil positioning results

Fixation Point Trajectory Calibration

The fixation position can be obtained by eye movement video, and the fixation position can be substituted into the mapping relationship as a known condition, then the corresponding fixation position on the screen can be obtained. According to the mapping model, the fixation point mapping function is obtained. Through this function, the coordinates of the calibration point and all fixation points can be described in the image coordinate system, that is, the mapping position image of the calibration point [11, 12]. The results of individual learning fixation trajectory annotation are shown in Fig. 6.

In Fig. 6, the "+" in red indicates the position of the calibration point obtained from the reverse mapping relationship, and the "·" in blue indicates the position of the fixation point obtained from the mapping relationship.

Blink Detection

Blinking is the process of upper eyelid from open state to closed state, and then from closed state to open state. In this process, the main change is the position of the upper eyelid. Due to the occlusion of the upper eyelid on the pupil, the pupil size first changes from large to small and then from small to large. Therefore, only the pupil size and eyelid height of each frame in the video image sequence are required to detect the blink [13].

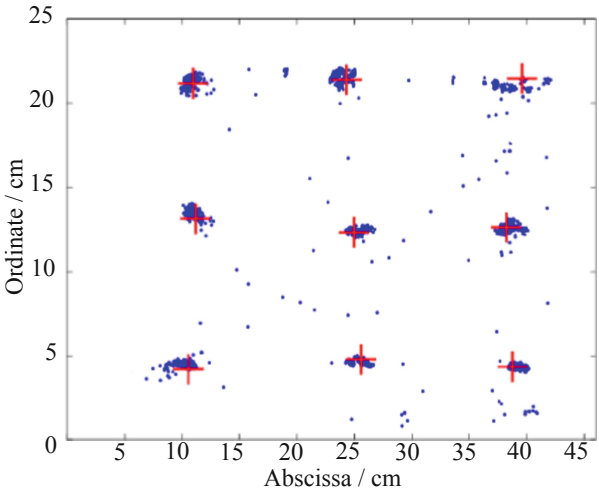

Fig. 6. Mapping position image of calibration point (Color figure online)

Blink detection is mainly divided into two steps: blink start position detection and blink end position detection. Firstly, the absolute value of the gray difference between the current frame and the previous frame in the video image is calculated, and a threshold is set. By comparing with the threshold, the absolute value image of the gray difference obtained before is converted into a binary image. The eye structure of eyelid can be obtained by processing the binary image. There will be small gaps and isolated points in the direct binary image of eyelid. A new threshold is set in advance, and the starting position of blink is determined by comparing the position of eyelids and the change of the width of eyelids in two adjacent frames. Find the frame with the largest eyelid width. In this frame, if the ratio of the width of the eyelid to the width of the whole eye image is greater than or equal to the previously set threshold, and the difference of the eyelid position is the largest, the frame is considered as the starting image of blinking.

With the start of blinking, the pupil area begins to decrease and the position begins to decrease until it disappears. When the eyes are opened again, the pupil area begins to enlarge and the position rises gradually. A pupil threshold is set in advance, and the position of blink termination is determined by comparing the pupil size and height of two adjacent frames. When the height of the pupil remains unchanged, the height is greater than or equal to the threshold of the pupil threshold, the ratio of the pupil width to height in the frame is between 0.3 and 3, and the ratio of the pupil size to the whole eye image is greater than or equal to the standard ratio, the frame is considered as the end image of blinking.

Combined with the above test results, the final conclusion is that Guo Chenzhong's concentration is as follows:

$$ZKD = \left(\frac{ZKDarea}{ZKDarea_{\max}} \right) \times 100\% \tag{9}$$

In the formula, *ZKDarea* and $ZKDarea_{\max}$ respectively represent the current student's eye opening and maximum opening. When the value of the tested target ZKD is greater than 20%, it can be judged that the probability of class concentration in the class is higher. When the value of the tested target ZKD is less than 20%, it can be judged that the probability of class concentration in the class is low.

2.6 Analysis of Individual Learning Action Trajectory

Set the page dwell time, the number of mouse clicks, the number of page revisits, and the number of slider movements as the constituent indicators of the personal learning behavior trajectory. The page dwell time is the time when the individual browses the online teaching webpage of the ideological and political theory course. Browse to the time to perform the close action to leave the page. The mouse click is defined as the sum of the number of clicks of the left mouse button and the right mouse button. Every time a user opens a new website page, it will be recorded. When a user opens the same page multiple times, the visit volume value increases, that is, the number of times the page is viewed [14, 15]. The sliding times of the slider is the sum of all basic events related to scrolling the webpage. Arrange the above-mentioned indicator data in chronological order to obtain the analysis result of individual learning action trajectory.

2.7 Realize Personal Learning Pattern Recognition

Based on the analysis results of two kinds of behavior data in online teaching of Ideological and political theory course, it is output in the form of feature vector, and compared with the matching standard of the individual learning mode type and behavior item. Through qualitative comparison and quantitative calculation, the final result of personal learning pattern recognition in online teaching of Ideological and political theory course is obtained.

3 Comparative Experimental Analysis

In order to test the recognition function and application performance of the personal learning pattern recognition model designed above, the following comparative experiments are designed. The contrast groups in the experiment are the traditional learning pattern recognition model based on random forest and the learning pattern recognition model based on data mining.

The hardware configuration of the workstation is i7-6700 CPU, 32 g memory and GTX 1080ti graphics accelerator. The software is developed based on Python 3.6 and python 1.0. The learning pattern recognition model applied in the experiment is adjusted by grid search method. In addition, the online teaching platform of Ideological and political theory course in a university is selected as the operation platform of the identification model.

In the experimental environment to collect personal learning mode data, the video data collection needs to ensure that the classroom in the real state of shooting, effectively recording the status of students in class, according to the light intensity of the shooting

scene to adjust the aperture coefficient, to ensure that the image is clear, in the recording, students are in a normal and relaxed learning state. The reference data set is set in the experimental environment to provide a comparative reference for the operation of the recognition model.

The recognition accuracy and application performance of the personal learning model are respectively set as the two evaluation indicators of the experiment. Among them, the recognition accuracy is mainly to set the actual personal learning mode of the students in the classroom, and to indicate the convenience of comparison with the recognition results in the form of numbers. In addition, the application performance test is to apply the recognition model to the actual online teaching work of ideological and political theory courses. After a period of application, analyze the students' ideological and political theory course test scores under different recognition models.

After statistics of relevant data, the test results of the recognition model are obtained, and the test results of the recognition accuracy are shown in Table 1.

Table 1. Accuracy test results of the recognition model

Research object number	Research object number	Output result of learning pattern recognition model based on random forest	Output result of learning pattern recognition model based on data mining	The output results of this model
1	Autonomous learning-1	Inquiry learning-2	Autonomous learning-1	Autonomous learning-1
2	Autonomous learning-1	Autonomous learning-1	Autonomous learning-1	Autonomous learning-1
3	Cooperative learning-3	Cooperative learning-3	Cooperative learning-3	Cooperative learning-3
4	Inquiry learning-2	Inquiry learning-2	Cooperative learning-3	Inquiry learning-2
5	Inquiry learning-2	Cooperative learning-3	Inquiry learning-2	Inquiry learning-2
6	Cooperative learning-3	Cooperative learning-3	Cooperative learning-3	Cooperative learning-3

It can be seen from Table 1 that, compared with the two comparison models, the output result of the recognition model designed in this paper is closer to the set personal learning mode without any misidentification, which indicates that the recognition model designed in this paper has a higher recognition accuracy.

On this basis, the identification model designed in this paper is applied to the actual teaching work of ideological and political theory courses, and 6 students are randomly selected as the research objects, and the scores of the most recent course examinations of the research objects are collected for comparison. During the application of the identification model Combine the recognition results to adjust the student's learning mode, and

after a period of study, obtain the student's test score data after applying the recognition model. The comparison of the student's performance before and after the recognition model is applied to prove the application performance of the recognition method and test results as shown in Table 2.

Table 2. Application performance test results of identification model

Research object number	Students' ideological and political theory course grades/points before the recognition model is applied	Students' ideological and political theory course grades/points after the recognition model is applied
1	76	87
2	84	95
3	82	93
4	79	89
5	85	91
6	77	94

As can be seen from Table 2, before the application of the recognition model designed in this paper, the average score of students in ideological and political theory course is 80.5. After applying the recognition model designed in this paper, the average score of students' ideological and political theory course is 91.5 points. By comparison, we can see that the recognition model designed in this paper can effectively improve students' achievement in ideological and political theory. It can be shown that the learning pattern recognition method designed in this paper can effectively guide students' learning patterns to the right direction and has high application value.

4 Conclusion

This study provides an effective auxiliary tool for online teaching through the optimization design of personal learning pattern recognition model of online teaching of Ideological and political theory course, which can indirectly improve the quality and effect of online teaching of Ideological and political theory course. However, due to the design of the recognition model mainly from two aspects of video data and behavior data for specific analysis and recognition, it needs to consume more recognition time, hoping to be optimized and improved in the future work.

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References

1. Chung, C.-C., Huang, S.-L., Cheng, Y.-M., Lou, S.-J.: Using an iSTEAM project-based learning model for technology senior high school students: design, development, and evaluation. Int. J. Technol. Des. Educ. **55**(3), 1–37 (2020). https://doi.org/10.1007/s10798-020-09643-5
2. Taufik, H., Yustina: Motivation and skills of science teachers' online teaching through online learning training in the covid-19 period in Pekanbaru Indonesia. J. Phys.: Conf. Ser. **16**(1), 12–22 (2020)
3. Chen, W., Tang, X., Mou, T.: Course design and teaching practice in STEAM education at distance via an interactive e-learning platform: a case study. Asian Assoc. Open Univ. J. **15**(7), 37–46 (2019)
4. Xu, Z., Zhao, J., Yu, Y., et al.: Improved 1D-CNNs for behavior recognition using wearable sensor network. Comput. Commun. **15**(1), 165–171 (2020)
5. Nguyen, N.G., Phan, D., Lumbanraja, F.R., et al.: Applying deep learning models to mouse behavior recognition. J. Biomed. Sci. Eng. **12**(2), 183–196 (2019)
6. Xu, K., Zeng, Y., Zhang, Q., et al.: Online probabilistic goal recognition and its application in dynamic shortest-path local network interdiction. Eng. Appl. Artif. Intell. **85**(10), 57–71 (2019)
7. Tan, Z., Xu, L., Zhong, W., et al.: Online activity recognition and daily habit modeling for solitary elderly through indoor position-based stigmergy. Eng. Appl. Artif. Intell. **76**(9), 214–226 (2018)
8. Fu, W., Liu, S., Srivastava, G.: Optimization of big data scheduling in social networks. Entropy **21**(9), 902 (2019)
9. Liu, S., Glowatz, M., Zappatore, M., et al. (eds.): E-Learning, E-Education, and Online Training. Springer, Heidelberg, pp. 1–374 (2018). https://doi.org/10.1007/978-3-319-49625-2
10. Liu, S., Li, Z., Zhang, Y., et al.: Introduction of key problems in long-distance learning and training. Mob. Netw. Appl. **24**(1), 1–4 (2019)
11. Ling, X.P., Zhang, R.J., Yan, Y.F.: Research on online and offline mixed teaching mode of ideological and political course in colleges and universities. Party Build Ideol. Educ Sch. **25**(10), 46–49 (2020)
12. Liu, Q., Chen, E.H., Zhu, T.Y.: Research on educational data mining for online intelligent learning. Pattern Recognit. Artif. Intell. **31**(01), 77–90 (2018)
13. Chen, J.F., Zhu, J.: Efficient learning algorithm for maximum entropy discrimination topic models. Pattern Recognit. Artif. Intell. **32**(08), 736–745 (2019)
14. Chen, J.Y., Wang, Z., Chen, J.Y.: Design and research on intelligent teaching system based on deep learning. Comput. Sci. **46**(S1), 550–554+576 (2019)
15. Tan, Z., Jiang, X.: Interaction design of e-learning platform based on the fogg's behavior model. Packag. Eng. **41**(04), 189–194 (2020)