similarity, that is similarity algorithm and improved cosine similarity algorithm.

4. Experimental analysis

In order to verify the accuracy of the proposed algorithm for the recommendation of sports online video teaching resources, the algorithm is built according to the algorithm design process and applied to a sports college.

In order to further test the recommended performance of the designed algorithm, 50 testers are selected to test the algorithm, all of whom are students majoring in physical education. The basic process of the test is as follows: Firstly, the user registers the algorithm, then logs in the algorithm, enters the personal center page, and fills in the personal basic attribute information. Then the course is browsed to select the course that you are interested in. People can also quickly select the courses in the navigation bar and start learning the courses. The system records the recommended resource information each time. In this test data set, a total of 50 students learn and score 20 sports online video teaching resources. The main purpose of this test is to test the recommendation effect of the algorithm. Due to the limitations of the experimental environment and conditions, the quality of the testers does not reach the expected effect, and the number is relatively limited, but the overall recommendation effect is relatively obvious, which reaches the expected value.

The proposed algorithm is used to recommend resources for users, first the average dwell time and mouse clicks of the algorithm users on the recommended resources are counted, and then 10 points as the scoring standard are selected to let students score the recommended sports online video teaching resources. The statistical results are shown in Table 1.

Table 1. Resource recommendation results

Tester serial number	Average time on page/s	Mouse clicks	score
1	10.52	6	7.5
2	11.64	7	8.1
3	12.34	8	7.6
4	12.84	6	8.2
5	13.64	5	8.4
6	10.85	7	8.4
7	13.46	7	7.8
8	14.58	9	7.3
9	16.52	8	7.2
10	13.45	8	7.5

It can be seen from the experimental results in Table 1 that the algorithm provides users with recommended resources. The average stay time of the user's page is more than 10s, the number of mouse clicks is more than 5, and the score of the recommended online sports video teaching resources is higher than 7 points, which verifies that the algorithm in this paper has high recommendation effectiveness.

The accuracy of sports online video teaching resources recommendation is extremely important. With the wide application of recommendation algorithms, the real effect and role of recommendation algorithms are extremely important. The accuracy rate and recovery rate and other indicators are used to measure the performance of the recommended resource algorithm. The accuracy rate refers to the ratio of the number of accurately recommended resources to the total number of recommendations. The higher the accuracy, the better the recommendation effect. Recall rate refers to the ratio of the number of accurately recommended resources to the total number of relevant resources. The higher the recall rate, the better the effect of resource recommendation. The F1 value is the metric that neutralizes precision and recall. The algorithm in Refs 11-12 are selected as comparison algorithms, and the comparison results of resource recommendation accuracy and recall of different algorithms are shown in Fig. 4 and Fig. 5.

In practical application, there is a high contradiction between accuracy and recall. In order to accurately evaluate the performance of resource recommendation, The F1 value measurement index is selected to calculate the evaluation result, and the F1 value of the online sports video teaching resources recommended by the three algorithms is counted. The statistical results are shown in Fig. 6.

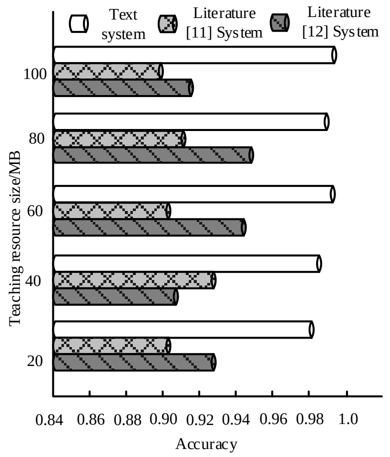

Figure 4. Precision comparison results

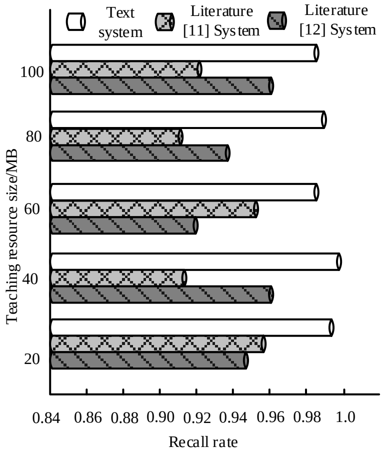

Figure 5. Recall comparison results

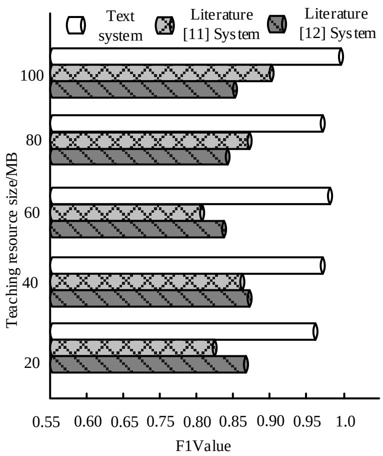

Figure 6. Comparison results of F1 values

Through comprehensive analysis of the experimental results in Fig. 4 -Fig. 6, it can be seen that compared with the other two algorithms, the recommendation algorithm adopted in this paper has a certain improvement in the recommendation success rate. The resource recommendation of the proposed method has an average accuracy of 98.21%, an average recall rate of 98.35%, and an average F1 value of 95.37%. With the increase of the number of recommended resources, the recommendation success rate of this algorithm does not decrease. Obviously, the recommendation success rate of this algorithm is higher than the other two algorithms. When the number of recommended resources increases to a certain extent, the recommendation algorithm will recommend more pages that are not related to learners' interests and preferences, and the recommendation success rate will inevitably decrease. In the case of a high number of recommended resources, the proposed algorithm can still maintain a high recommendation accuracy, which verifies that the proposed algorithm has a high recommendation performance.

In order to further verify the recommended performance of the algorithm in this paper, MAE (Mean Absolute Error) is selected as another evaluation standard for the recommended performance of the algorithm. At present, almost all researches on personalized recommendation choose MAE as the evaluation standard, and MAE can determine whether the recommendation is accurate by comparing the degree of deviation. The deviation degree refers to the result of predicting the user's real score by the recommendation algorithm. The lower the MAE value is, the smaller the deviation between the estimated score and the actual score is, and the more accurate the recommendation is. When the MAE is high, it indicates that the error is large and the effect of the recommendation is poor. The number of resources scored is defined by the user as n, the algorithm predicts that the user's score on the resource i is X, and the actual score on the resource i is Y, then the calculation formula of MAE is as follows:

$$MEA=\left(\sum_{i=1}^{n}\left|x_i-y_i\right|\right)/n \tag{7}$$

The MAE comparison results of online video teaching resources recommended by the three algorithms are shown in Figure 7.

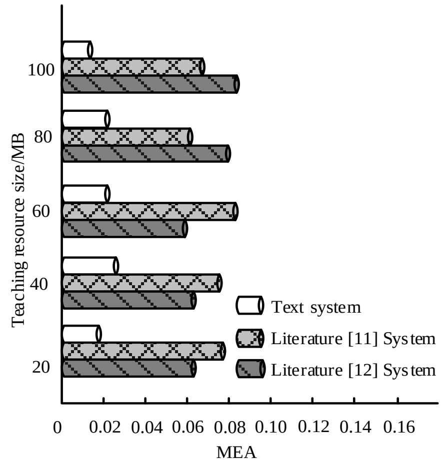

Figure 7. MEA value comparison results

As can be seen from Figure 7, with the increase of the number of online video teaching resources, the average absolute error of the algorithm in this paper is still significantly higher than that of the other two algorithms, which indicates that the error of the recommendation algorithm used in this paper is smaller than that of the other two algorithms and the recommendation result is more accurate when the number of users continues to increase.

Performance testing is a key step to ensure the quality of algorithms. Good performance testing can find problems in time, solve hidden dangers, provide more security, predict possible load problems and concurrent problems, and optimize the code in advance to make a good response plan.

The performance test indicators of this algorithm are described in detail below.

(i) Concurrent number refers to the number of all users performing the same operation at the same time.
(ii) Average response time refers to the average transaction processing time per second during the test. This indicator test can reflect the number of transactions in different reaction times during the test.
(iii) Average running time refers to the average time that transactions are actually executed at each time in the test. This method can analyze the performance trend of the algorithm.
(iv) Throughput refers to the number of transactions per second of the server during the test execution. Its unit of measurement is one byte, which represents the amount of data obtained by the virtual user from the server at any given time per second.
(v) Transaction overview refers to judging the success and failure of user transactions during the test.
(vi) Network transmission rate refers to the average traffic per second of the network, which is used to detect whether there is a response of network delay caused by excessive network traffic.

When the number of concurrent users is 500, the test results of various performance indicators of the algorithm are shown in Table 2.

Through the performance test results, it can be seen that the performance index values of the algorithm are not significantly different under different concurrent numbers, and the overall state of the algorithm is relatively stable. Although it is normal for the algorithm to run slowly when a large number of users access the algorithm at the same time, the algorithm in this paper still has access failure, because there are two access failures when the concurrent number is 500. This shows that the algorithm still has room for improvement and optimization. In order to achieve better performance, maintenance and optimization are required in the later stage. .

Table 2. Algorithm performance index test results

Concurrent number	Average response time/ms	Average running time/ms	Throughput/ Mbps	Network transfer rate/(kb/s)	Business summary
50	58.64	231.52	9.52	345.62	success50
100	63.85	256.46	10.54	411.65	success100
150	72.54	285.64	11.64	456.85	success150
200	81.64	305.52	12.58	496.52	success200
250	92.64	356.46	13.64	534.65	success250
300	101.25	398.54	14.85	584.52	success299
350	126.54	425.61	16.85	654.85	success349
400	134.52	495.64	17.84	702.54	success399
450	156.48	581.52	18.56	756.84	success448
500	195.64	684.56	21.56	815.32	success498

4. Experimental analysis

Individualized learning is the basic trend of the development of physical education in the future, and how to guide students to individualized learning is a research hotspot. In order to meet the individual needs of online learning of physical education students, this paper designs an accurate recommendation algorithm for online sports video teaching resources based on collaborative filtering, and personalized recommendation technology is applied to the field of online sports learning. After receiving the data, the data layer of the entire recommendation algorithm stores the video in the database and transmits it to the business processing layer at the same time. The business processing layer utilizes the designed collaborative filtering resource recommendation algorithm. The recommendation results are formulated for different users, and the recommendation results are pushed to the user display interface of the user layer. It is hoped to provide ideal learning resources for students' personalized sports learning. The algorithm uses collaborative filtering recommendation algorithm to recommend sports online video teaching resources for users. The recommendation is mainly based on collaborative filtering recommendation algorithm, which converts user attribute feature values into interest models, and calculates neighbor users according to the interest models, thus improving the problems of user cold start and data sparsity. The resource recommendation algorithm based on the above recommendation algorithm includes the functions of browsing courses, course learning, recommending sports online video teaching resources, and managing sports online video teaching resources.

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