Personalized Recommendation Method for the Video Teaching Resources of Folk Sports Shehuo Based on Mobile Learning

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Abstract. Xunxian Shehuo is a kind of sports project which gathers many kinds of folk customs, and it is the key to develop the national fitness strategy. Folk sports social fire video teaching resources are so large that it is difficult for learners to find the content they are interested in from a lot of information. Based on mobile learning theory, this paper constructs a learner model by analyzing learner characteristics, collecting learner data and representing learner characteristics. Weighted the learner behavior, obtained the characteristics of learner interest preferences, and calculated the similarity between learner interest preferences and teaching resources. Through collaborative filtering recommendation algorithm to obtain the best teaching resources personalized recommendation results. The experimental results show that the maximum recall rate and the maximum accuracy rate are 96% and 98%, which fully proves the effectiveness of the proposed method.

Keywords: Mobile Learning · Folk Sports · Social Fire Video · Teaching Resources · Personalized Recommendation

1 Introduction

The Xunxian Shehuo has a long history and profound cultural background, which fuses excellent folk sports items in different periods. Nowadays, Xunxian Shehuo are numerous and in different forms, and at the same time meet the needs of different age groups for physical exercise. In order to promote the orderly implementation of the national fitness strategy, improve people's living standards and physical fitness.Folk sports is an important part of national fitness, and social fire activities is an indispensable part of folk folk sports to show style [1]. At the same time, it is also proposed to "vigorously develop sports popular with the masses, encourage the development of sports with characteristics suitable for different groups and regions, and support the promotion of Taijiquan, fitness qigong and other ethnic and folk traditional sports".

At present, the main activities of Xunxian Shehuo County include lion dance, dragon dance, Danhua basket dance, Yangko dance, dry boat dance, stilt dance, bamboo dance, dragon lantern dance, pavilion dance, waist drum dance, drum dance, etc. Making use of

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these contents of folk physical exercise can not only effectively promote the implementation of national fitness strategy in the folk. Moreover, social activities can better adapt to the new situation of the improvement of living standards and rapid economic development after integrating entertainment, fitness, leisure and tourism. Extensive development of folk social fire sports activities, on the one hand, is the reality of the majority of people's pursuit of folk beliefs, on the other hand, the desire to achieve high-quality life of the real exposure. Compared with Western sports projects, Xunxian Shehuo has its unique advantages because of its distinctive regional features, broad public base and long history. In the development of the new era, these advantages can be fully utilized to serve the general public.

With the wide application of the Internet and the rapid development of network education, network teaching resources increase exponentially, especially folk sports social video teaching resources. The popularization of network provides every learner with the ability to obtain the information of teaching resources anytime, anywhere. People pay more and more attention to the co-construction and sharing of digital educational resources, and the demand for high-quality educational resources is increasing. The country also lists the construction of digital education resources as the focus of education information development. At the same time, it puts forward the idea of "bringing modern information technology into full play to promote the sharing of high-quality teaching resources". In recent years, governments at all levels, together with related units, have invested a lot of resources in the construction of educational resources for folk sports.

At present, the construction of digital education resources platform has become an important part of education information and a hot practice. It incorporates modern information technology and is characterized by digitalization, multimedia, networking and intelligence [2]. Digitization transforms complex educational information into measurable numbers or data. Multimedia provides more forms for information exchange in teaching process. Network makes educational resources can be shared, and educational activities are not limited by time and space. Intellectualization makes the teaching behavior humanized. Through the use of digital education resources platform, in addition to break through the traditional way of education in time and space constraints, to provide flexible learning methods. It also provides learners with rich and high-quality educational resources and creates more learning opportunities and better learning environment. However, more and more convenient access to information, but also a series of problems. Every day a large number of pictures, videos, text and other teaching resources have been published on the network. With the rapid accumulation of these information, it is difficult for learners to find their own interesting content from a lot of information, which seriously reduces learning efficiency and resource utilization. In order to overcome the problem of "information overload" caused by mass educational resources, this paper puts forward the personalized recommendation method of folk sports social fire teaching resources based on mobile learning. Based on the mobile learning theory, this paper collects learner characteristic data and characterizes learner characteristics, and builds a learner model. According to the characteristics of learners' interest preferences, the similarity between learners' interest preferences and resources is calculated. The collaborative filtering recommendation algorithm is used to obtain the best personalized recommendation results of teaching resources.

2 Research on Personalized Recommendation Method of Video Teaching Resources in Folklore Sports Club

2.1 Construction of Teaching Resources for Mobile Learning

There is no definitive consensus on the definition of mobile learning. Experts and scholars in the field have given different definitions from different perspectives. Through in-depth analysis, we can see that “learners learning anytime, anywhere” is considered as the core characteristics of mobile learning. According to several scholars, mobile learning is defined as the use of mobile terminal devices by learners. With the support of mobile communication technology, learning mode of anytime and anywhere is an extension of digital learning. The position of mobile learning in the learning style is shown in Fig. 1.

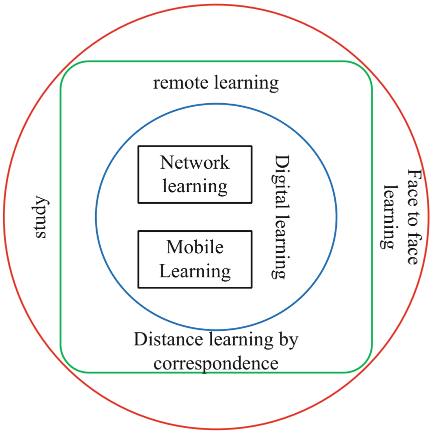

Fig. 1. Schematic diagram of the position of mobile learning in learning methods

As shown in Fig. 1, mobile learning is a new learning model for distance learning. It is based on the development of digital learning, digital learning is an expansion of “distance education” and “digital learning” understanding can help us better grasp the mobile learning. The realization of mobile learning mode is based on intelligent mobile terminal, mobile communication technology and Internet technology. The development of software and hardware constitutes the mobile learning environment. It is also an important factor to promote the development of mobile learning. Mobile learning has the characteristics of digital learning, its core features, but also its unique and unique characteristics are: its learning environment is mobile, learning is very flexible, can help learners learn anytime, anywhere. At the same time, because the intelligent mobile terminal is private to each learner, it can realize personalized learning more easily. To grasp the definition and connotation of mobile learning is an important theoretical basis for building high-quality mobile learning resources.

Mobile learning is based on digital learning, effectively combined with mobile technology, bring learners a new feeling of learning anytime, anywhere. Mobile learning is widely recognized as an indispensable learning model for future learning, with the following main features:

(a) Mobility

Mobile learning tools are intelligent mobile terminals, which make the learning activities of learners not limited to a fixed context, learning activities can occur at any time, any place. Learners can learn anywhere and anytime through mobile devices, as well as access to information on the Internet through wireless networks.

(b) Personalise

Learners' foundation, motivation and style are different. Teaching students in accordance with their aptitude is a concept pursued by educationists in past dynasties. Traditional education has its congenital deficiency in this regard. However, the differences between the private nature of mobile terminals and learners' personalities doomed mobile learning to have personalized characteristics. Mobile learning is not just about enabling learners to learn anywhere, anytime. It can also help learners to customize their learning content, pace and progress according to their interests, characteristics and needs.

(c) Situational

Learning is not only the passive acceptance of knowledge, but also the internalization of knowledge, that is, the construction of new knowledge based on the original knowledge. According to the Situational Cognition Learning Theory, only in meaningful practical situations can learning be a real learning, can we really promote the construction of knowledge and help learners to master knowledge. In the process of mobile learning, learners may be in any practical situation, they can learn knowledge and understand the essence of knowledge according to the problems in real life.

(d) Collaborative

In the process of distance learning, emotional education in the process of learning has always been a matter of concern. In mobile learning, learners can share resources and communicate efficiently based on various channels of mobile network, and can also interact face-to-face. Secondly, the feedback and evaluation between learners and teachers are flexible and diverse. The learners' learning effect on the knowledge content and the affective factors in the learning process can be solved in time.

Based on the description of the above content, based on mobile learning theory to build folk sports social video teaching resources. It needs to meet the usability of strong, anytime and anywhere learning needs, to enhance learner autonomy and other principles. The structure of the construction model of mobile learning teaching resources is shown in Fig. 2.

According to the process shown in Fig. 2, the construction of mobile learning teaching resources is completed. It lays a solid foundation for the realization of personalized recommendation of subsequent teaching resources.

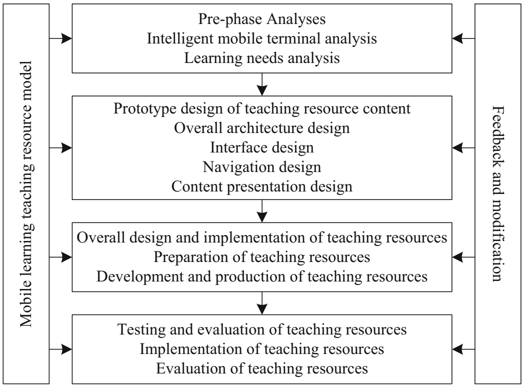

Fig. 2. Structure diagram of mobile learning teaching resources construction mode

2.2 Learner Model Building

Learner model is the basis of personalized recommendation system of folk sports social fire video teaching resources, and provides the essential basis for personalized service demand. Through a more in-depth study of learners to select folk sports social fire video teaching resources of various factors. It can better capture the personalized needs of learners with different learning goals and preferences for teaching resources [5]. When the learners choose the video teaching resources of folk sports in network environment, they are influenced by the time, place, platform, teaching resources and client. The internal factors such as cognitive ability, knowledge mastery and interest preference play a decisive role. Therefore, this research mainly embarks from learner's own characteristic, completes the learner model the construction. The process of building the model includes the analysis of learner characteristics, the collection of learner data and the representation of learner characteristics. The model provides a basis for personalized recommendation of teaching resources.

Learner Characteristics Analysis

The learner model in personalized recommendation of teaching resources is studied. It is found that there are some problems in the present learner modeling, such as incomplete description of learner characteristics and preference information. This research aims at the above questions, the union learner actual application situation, according to the study style theory. Part of the existing learner model specification is expanded and re-classified. Four characteristics, including basic information, learning style, cognitive level and interest preference, are used to describe the learner model. As static data, the basic information is invariable and common, and can not express the degree of learners' personalized characteristics. Therefore, this study will not focus on data analysis. Through describing the three characteristics of the learner model, a multi-level personalized learner model is designed. The model consists of four layers: data acquisition layer, data analysis layer and presentation layer. The learner model building process is shown in Fig. 3.

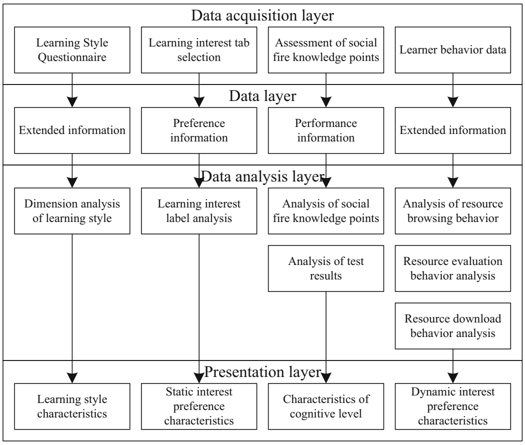

Fig. 3. Learner model building process diagram

As shown in Fig. 3, this section clarifies the learner model building process. Provide support for subsequent learner data collection and feature representation.

Learner Feature Data Collection

Learner characteristic data is the data base of learner model. Therefore, for the construction of the model, data is essential and important information, the determination of learners' personalized characteristics is based on data collection as a starting point. In this study, the basic information, learning style and initial interest preference characteristics of the learner model are obtained by registration, questionnaire and questionnaire. The characteristics of dynamic interest preference and cognitive level are that the computer accesses the system Web logs to dynamically obtain the learners' learning behaviors and their results during the learning process [6]. According to the four characteristics of the learner model, the learner database of the course learning platform is collected. It provides a data base for the representation of personalized features in the learner model. Learner information includes: basic information, learning style information, initial interest information, learning behavior information, assessment data information.

Among them, the basic information is manually entered by the learner registration system. As static data, basic information is invariable and common, which can hardly reflect the individuation degree of learners. Therefore, this study will not focus on data analysis.

Store student learning style data in a database. This part of information can reflect the learner's preference for the type of resource media and the abstract level of the resource content. Assign the questions and answers to different codes. Question stem code by α_i, each question contains two answers (A, B). Then the answer to question α_1 is expressed in β_1 and β_2. By analogy, i-question stem, the answer contains $2i$ answer code, each answer corresponding to different dimensions. Learning style information is the basic data for the subsequent dimension analysis of learning style.

When the learner registers as a new user, the system provides a standardized tag feature library composed of resource features. Learners according to individual needs to check the interest of the way the knowledge tag. This part of the information reflects the learners' initial preference for learning resources, which belongs to static information. Learner's initial interest label record table is the basic data for subsequent interest analysis.

Learner's assessment data, including the learner's name, learning resources, resource names, depth of investigation and so on, are stored in the learning resource database. After the learner registration system completes the learning of each chapter, the result of knowledge point answer is obtained through knowledge point test as the data basis for analyzing learning cognitive level. The test questions of social fire knowledge come from the test questions database of learning resource model. Through the analysis of learners' knowledge points and the results of their answers, we can get the learners' grasp of learning resources in the actual learning process, that is, learners' learning cognitive level [7].

Learners' learning behavior information starts from the user login recommendation system. Learners record their whole learning behavior in the process of autonomous learning using learning resources. Learners' Web log will get the Learners' access to resources time, duration of continuous learning, learned resource coding, test time, the frequency of clicking test questions. The learner's learning behavior data can not only reflect the learner's preferences, but also can be related to the characteristics of learning resources. This part of information is used as the data base to analyze the dynamic characteristics of learners' interest in learning resources.

Based on the description above, the corresponding learner characteristic data are collected to provide data support for the learner model construction.

Learner Feature Representation

This research chooses Felder- Silverman style model as the theoretical guidance. The matching Solomon Learning Style Scale was used to measure learners' learning styles. Firstly, learning style is divided into four dimensions: perception, input, processing and understanding. Then we analyze two different styles and their preferences in each dimension of the four dimensions to show the individual learning style characteristics. Learners are tested by questionnaires when they enter the recommending system of teaching resources. Based on the questionnaires, the features of learning style are static. The specific process of acquiring learner style features is as follows:

Step 1: Learners' learning styles are described in terms of four dimensional vectors to describe the style types and learning style propensity values in four different dimensions. The expressions are:

$$\chi = \{(\langle\delta_1, \varepsilon_1\rangle, \langle\delta_2, \varepsilon_2\rangle, \langle\delta_3, \varepsilon_3\rangle, \langle\delta_4, \varepsilon_4\rangle)|\varepsilon_i \in [-1, 1]\} \quad (1)$$

In formula (1), χ refers to the learner's learning style. $\langle\delta_i, \varepsilon_i\rangle$ represents the values of four different dimensions. δ_i represents a dimension. ε_i represents the values corresponding to the learning style dimension δ_i.

Step 2: When learners fill out the Salomon Style Questionnaire, there are two choices for each question. The result of the answer is defined as ϕ_{ij}, the result of each question is φ, i is the item number, j is the result of selection, and the value in the computer is 1 or 0.

Step 3: When the learner has completed the questionnaire and submitted the answer data, the computer begins to analyze the data retrieved from the database. The results of four dimensions were screened, the number of j was classified and accumulated, and the final results were represented by C and D.

Step 4: The scale is used to determine the size of C and D. The formula for calculating the difference is as follows:

$$\gamma = C - D \tag{2}$$

In formula (2), γ represents the difference between C and D.

Based on the result γ of formula (2), if $\gamma \geq 0$, transpose step 1. If $\gamma < 0$, the result γ will be passed to ϕ_{ij}, you can get specific learning style conclusion.

Step 5: According to the final test results expressed as quadruples. Pass to the database to get the learner's learning style characteristics.

The above process completes the construction of learner model, and makes sufficient preparation for personalized recommendation of teaching resources.

2.3 Interest Preference Feature Acquisition

Based on the learner model, the learner behavior is weighted. Based on this, the characteristics of interest preference are obtained to provide reference for personalized recommendation of follow-up teaching resources [4].

The behavior of each learner to each folk sports social fire video teaching resources can reflect his preference to resources. Based on the weight of each operation behavior, this section presents a weighted representation of the learners' preferences for different labels. Create a learner -tag matrix with the following expressions:

$$\lambda_{m\times n} = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1n} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2n} \\ \vdots & \vdots & \lambda_{ij} & \vdots \\ \lambda_{m1} & \lambda_{m2} & \cdots & \lambda_{mn} \end{bmatrix} \tag{3}$$

In formula (3), $\lambda_{m\times n}$ represents the learner -tag matrix. λ_{ij} represents the cumulative behavior weights of the learner u_i on the instructional resource label t_j.

Based on the learner's preference analysis of single resource label and the representation of learner -resource scoring matrix. Interest preference characteristics of a single learner based on learning behavioural weights for all historical resources will now be analysed [8]. Known sets of teaching resources, learner behavior, and labels are X, Y, and T. In addition, time factor can be introduced to adjust learners' interest bias. In this algorithm, learners' characteristics based on time parameters are defined. The idea of adaptive time attenuation function and Ebbinghaus forgetting curve are adopted. The formula for learners u_i and labels based on the time factor is:

$$f^{time} = \vartheta + (1 - \vartheta)e^{-\left(d_1 - d_{t_j}\right)} \tag{4}$$

In formula (4), f^{time} is the value of the time weight. ϑ represents auxiliary parameters. With the decrease of ϑ value, time factor has more influence on learners u_i and label t_j. d_1 is the current time. d_{t_j} indicates the last time that tag t_j marked learner u_i.

Based on the above analysis, the characteristic vector expression of learner interest preference is:

$$\eta_{u_i} = \frac{\lambda_{m\times n} \cdot \omega_i}{\tau' * f^{time}} \tag{5}$$

In formula (5), η_{u_i} is the characteristic vector of learners' interest preference. ω_i represents the weights of learner behavior. τ' is the cofactor of interest preference feature acquisition, whose value range is [1, 10].

The above process completes the acquisition of learners' interest preference features, and provides support for the implementation of personalized recommendation of subsequent teaching resources.

2.4 Personalized Recommendation of Teaching Resources

Based on the above obtained interest preference feature vectors. The similarity between learners' interest preferences and teaching resources and the connection between teaching resources are calculated. Through collaborative filtering recommendation algorithm to obtain the best teaching resources personalized recommendation results.

There are many ways to calculate the similarity between learners' interests and teaching resources. Collaborative filtering of learner data is based on learner data that have had common behavior with teaching resources. Cosine similarity is used to calculate the similarity between learners' interests and teaching resources. The formula is as follows:

$$\mu\left(\eta_{u_i}, X_j\right) = \frac{1}{\hat{\sigma} \cdot N(u_i)} * \frac{\omega_i \cdot \omega_j}{|\omega_i| \cdot \left|\omega_j\right|} \tag{6}$$

In Formula (6), $\mu\left(\eta_{u_i}, X_j\right)$ indicates the similarity between η_{u_i} and j Teaching Resource X_j, which is the preference of u_i learners. $\hat{\sigma}$ represents the similarity factor and needs to be set according to the actual situation. $N(u_i)$ represents the total number of learners u_i. ω_j represents the weight coefficient of the j teaching resources.

In the calculation of similarity, the higher the similarity value $\mu\left(\eta_{u_i}, X_j\right)$ of teaching resources and learners' interest preference is, the closer the teaching resources and learners' interest preference are. Then this teaching resources are worth recommending.

The connection between teaching resources is used to measure the close relationship between teaching resources. On the recommendation of teaching resources, the more closely the students' cognitive knowledge points are connected with the teaching resources. The more this resource meets learners' learning needs, the more it is recommended.

For the same teaching resources include knowledge points, we believe that two knowledge points in the path of equal status. That is, there is no sequence of two knowledge points, their shortest path distance set to 1. If there is no path between X_j and X_k or X_j and X_k are the same knowledge point, set the shortest path distance to 0. When there is no path between two teaching resources, there is no direct relationship between them. When the two teaching resources are the same, it is considered that the learner has already learned the teaching resources and there is no need to repeat the learning, so the shortest path is set to 0 [9]. Remove the above from any two teaching resources X_j and X_k. Their shortest path distance is the shortest path distance that can be retrieved. The formula for calculating the connection degree ζ_{jk} of teaching resources is:

$$\zeta_{jk} = \begin{cases} 0 & X_j = X_k \\ 1 & X_j, X_k \in KX_i \\ \frac{d(X_j, X_k)}{d^0} & other \end{cases} \tag{7}$$

In Formula (7), KX_i represents the i-type of teaching resources. $d(X_j, X_k)$ is the path distance between X_j and X_k. d^0 represents a unit of path distance to measure auxiliary parameters.

Based on the calculation result ζ_{jk} of formula (7), the connectivity between X_j and X_k of teaching resources shall be determined. The formula shall be:

$$\Phi(X_j, X_k) = \begin{cases} \frac{in|X_k|}{\zeta_{jk}} & \zeta_{jk} \neq 0 \\ 0 & \zeta_{jk} = 0 \end{cases} \tag{8}$$

In Formula (8), $\Phi(X_j, X_k)$ represents the connection between teaching resources X_j and X_k. $in|X_k|$ is the degree of X_k.

Based on the above calculated similarity between learners' interest preference and teaching resources, the connection between $\mu(\eta_{u_i}, X_j)$ and teaching resources is calculated as $\Phi(X_j, X_k)$. Based on collaborative filtering recommendation algorithm, the personalized recommendation results of the best teaching resources are obtained.

In order to make better recommendation of folk sports social video teaching resources, and avoid the shortcomings of collaborative filtering algorithm based on learners and teaching resources. This study proposes the following algorithms, which combine learner -based and instructional resource-based collaborative filtering algorithms. The hybrid recommendation model is used to complete the personalized recommendation of teaching resources. The specific steps are as follows:

Step 1: Input learner-instruction resource matrix.

Learners a teaching resource matrix recorded as $W(u_N, X_M)$. Among them, N represents the total number of learners, M represents the total number of teaching resources. The element W_{ij} corresponding to column j in line i of the matrix represents the learner u_i's rating of instructional resource X_j. If the learner u_i does not grade the instructional resource X_j, set the corresponding element to null.

Step 2: Formation of similar teaching resource sets.

For any resources X_j and X_k in the teaching resources, get the connection degree $\Phi(X_j, X_k)$. Generally speaking, in the process of teaching recommendation, the relationship between teaching resources will not change much within a certain time range. Therefore, the connection degree $\Phi(X_j, X_k)$ between teaching resources can be calculated offline in advance. And stored in a special database table, regularly updated. For any teaching resource X_j, search on the whole teaching resource set and select the first

l teaching resources with the largest connectivity $\Phi(X_j, X_k)$. It is integrated to obtain similar teaching resources.

Step 3: Formula (6) is used to calculate the similarity $\mu(\eta_{u_i}, X_j)$ between learners' interests and teaching resources. Combined with the score results of learner u_i on teaching resource X_j. Select appropriate teaching resources to recommend to corresponding learners.

Through the above process, the personalized recommendation of video teaching resources of folk sports club fire can be realized. Provide assistance for the development and promotion of Shehuo folk sports.

3 Experiment and Result Analysis

3.1 Experimental Condition Settings

In order to verify the application performance of the proposed method, 10 different experimental conditions were set to improve the accuracy of the experimental conclusions. The experimental conditions are set up as shown in Table 1.

Table. 1 Experimental condition setting table

Condition number	Number of teaching resources/piece	Number of learners
1	2356	124
2	3012	258
3	4015	345
4	2894	201
5	2101	198
6	2548	154
7	3057	320
8	3491	426
9	5201	388
10	5478	295

As shown in the data in Table 1, in the 10 experimental conditions, the number of learners is different from the number of video teaching resources of Folklore Sports Club. It meets the needs of personalized recommendation experiments for teaching resources.

3.2 Determination of Experimental Parameters

The parameter $\hat{\sigma}$ determines the calculation accuracy of the similarity between learners' interest preferences and teaching resources. Therefore, it is necessary to determine its optimal value before the experiment to ensure the best performance of the proposed method.

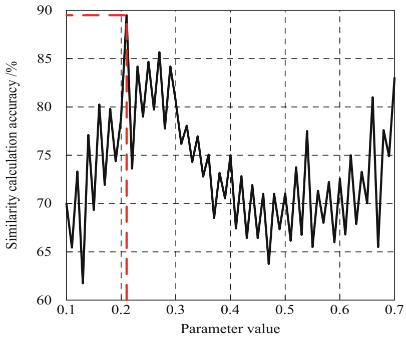

Fig. 4. Schematic diagram of the relationship between parameter $\hat{\sigma}$ and similarity calculation accuracy

The relationship between the parameter $\hat{\sigma}$ and the similarity calculation accuracy is shown in Fig. 4.

As shown in Fig. 4, when the parameter $\hat{\sigma}$ value is 0.21, the calculation accuracy of the similarity between the learner's interest preference and the teaching resource reaches the maximum value of 89.5%. Therefore, it is determined that the optimal value of parameter $\hat{\sigma}$ is 0.21.

3.3 Analysis of Results

Based on the experimental conditions set above and the determined experimental parameters, a personalized recommendation experiment of teaching resources is carried out, and the recall rate and accuracy rate are selected as evaluation indicators. Among them, the recall rate is the ratio of the number of teaching resources preferred by learners in the recommendation result set to the number of teaching resources preferred by all learners. The accuracy rate is the ratio of the number of successful recommendation results to the number of all recommended teaching resources. Under normal circumstances, the larger the recall rate and the accuracy rate, the better the personalized recommendation effect of teaching resources. On the contrary, the smaller the recall rate and the accuracy rate, the worse the personalized recommendation effect of teaching resources.

The recall and accuracy data obtained through experiments are shown in Fig. 5.

As shown in Fig. 5 (1) data, the recall rates obtained by applying the proposed method are greater than the given minimum limit, with the maximum reaching 96 per cent. As shown in Fig. 5 (2) data, the accuracy rates obtained usby aing the proposed method are greater than the given minimum limits, with the maximum reaching 98 per cent. The experimental results show that the proposed method has a higher recall and accuracy than the given minimum, which fully proves the effectiveness and feasibility of the proposed method.

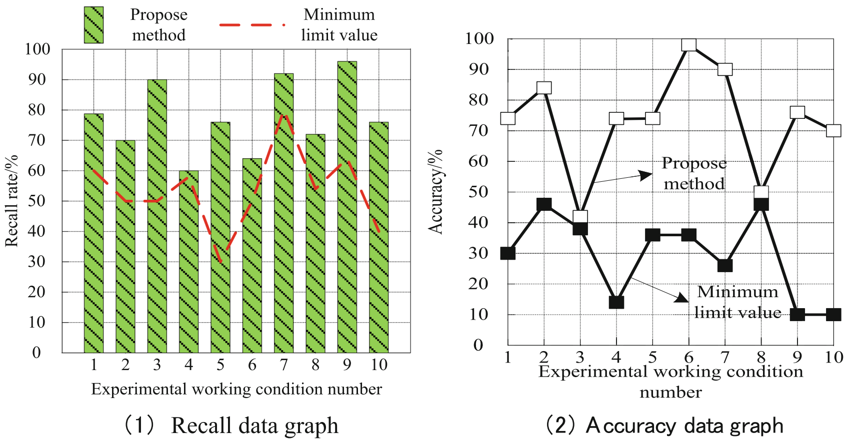

Fig. 5. Recall and precision data graph

4 Conclusion

In order to improve the accuracy of the recommendation of folk sports community fire teaching video resources. This study introduces the theory of mobile learning and proposes a new method of personalized recommendation of teaching resources in folk sports communities. By analyzing the characteristics of learners, a learner model is constructed. Based on the similarity between learners' interests and resources, the collaborative filtering recommendation algorithm is used to obtain personalized recommendation results. The experimental results show that the recall rate and accuracy rate of this method are higher than 96%. It not only contributes to the dissemination of folk sports social fire videos, but also provides support for the development of folk sports. In the subsequent research, we will consider collecting the implicit scoring information of users, such as users' favorites, browsing time, download records, etc., to reduce the dependence on users' explicit scoring.

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