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AI-driven personalized training model for dance movement and health management research

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ABSTRACT

In this paper, a personalized scheme recommendation method for dance movements based on ontological similarity is proposed. An ontology model of trainers is established, and in order to explore the interactions between trainers' attribute features and their influence on core parameters, SWRL rules are established using Jena inference engine for the inference of core parameters of training programs. The similarity degree is calculated according to the different types of user variables respectively, and the artificial neural network model is used to determine the degree of similarity between different trainers, in order to complete the recommendation of personalized training programs for dance movements. And then the requirements of the system are summarized to achieve the framework construction of the personalized dance movement training program recommendation system to achieve the health management in the training process. The recommendation effects presented by the similarity calculation method of this paper have reached the design goal of this paper, and the personalized recommendation system of this paper has also significantly improved the physical fitness level and the performance effect of dance skills of the experimental group of dance trainees, and the success rate of the kicking back leg movement has reached 91.67%. However, the system's function of improving health knowledge and health awareness needs to be further upgraded.
Keywords: ontology model; similarity calculation; neural network model; personalized training recommendation; dance movement

1. Introduction

Dance training is a basic component of dance education and teaching system, but also an important means of training dance professionals, and its scientific level not only affects the effect of dance education, but also determines the quality and level of training dance professionals [1-2]. At present, the public's appreciation of dance performance and dance movement technology is increasing, and the physical ability and movement technology level of the dancers have put forward higher and higher requirements [3-4].

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Entering the new era, "AI+Education" mode is highly favored by education groups because of its timeliness, interestingness and other advantages. Based on this, many dance teachers try to introduce it into dance teaching to optimize the teaching mode, enrich the teaching content, and enhance students' learning experience [5-6]. At present, the teaching mode has made initial progress, while the attitude of students to learn dance has also greatly improved, and can find a suitable path for personal dance development in a timely manner, the core competitiveness has been improved. In the new situation, "AI+Education" has formed a new educational trend, which organically integrates the teaching method of "online+offline" and has been supported by relevant policies [7-9]. The rapid development of information technology has promoted the emergence of several mature network platforms, and the field of dance education is no exception, such as Rhythmic Beauty App (app), Elephant Dance, and Dance with Heartbeat AI and other platforms are gradually emerging [10]. Applying various types of dance software developed for Chinese students in curriculum teaching can enrich students' dance learning content, take into account the specific needs of different students for diversified dance modules, enable students to make full use of the existing network resources, narrow the gap with their classmates, consolidate the dance theory and skill system, and promote the long-term development of their own dance learning [11-13].

In addition, all kinds of dance forms change, complex requirements, teachers need to invest a lot of energy to give students guidance and demonstration, resulting in less time for students to practice, correction and improvement, so that most students can only rely on their own perception to carry out systematic learning, but the learning effect is often poor, and over time, it will make a group of weak foundation, learning ability of the students and other students to produce a disconnected difference, the loss of continuous motivation to learn dance [14-15]. In order to change this situation, it is necessary to actively promote the reform of the dance curriculum, introduce the "AI+Education" model, provide more directions, space and possibilities for curriculum reform, provide online training and guidance platforms, prepare personalized practice guides, and promote students' systematic and refined practice of dance, thus improving the overall level of students' dance [16-17].

Sun, D conceived a classification framework based on features and data types, which outperforms traditional classification methods and improves the accuracy of movement recognition in the dance training process with artificial intelligence [18]. Wang, Y et al. analyzed the positive role played by AI technology in the dance training process and established a performance analysis model based on fuzzy interval number, grey system theory, and hierarchical analysis to achieve an accurate assessment [19]. Cao, X conducted a teaching comparison experiment and demonstrated that additional online extracurricular dance activities are important for dance skill enhancement [20]. Wang, J et al. analyzed mechanical injuries in dance training with artificial intelligence in a study and found that a variety of factors, such as the standardization of dance training, training intensity, and individual differences, led to mechanical injuries in the human body [21]. Wang, Z explored the performance of AI immersive technology empowering dance training, noting that such technology helps students' dance skill development and teaching improvement [22]. Xu, L et al. envisioned a dance teaching model combining AI technology and evaluation and visual feedback (DSTEVF) system, and confirmed in comparative assessment experiments that the said teaching model is more motivating to students' dance learning and effectively improved dance skills [23].

This paper proposes a personalized training program recommendation method for dance movements based on ontological similarity, and a personalized dance training recommendation system is constructed on this basis. A trainer ontology model is established based on user information, which is used to mine the implicit relationships among the attributes of the trainer ontology. The formal rule language SWRL was used to transform the implied relationships into digitally processable logic rules, and the core parameters of the training program were obtained using the Jena inference engine. This approach resulted in a more comprehensive picture of the trainer's situation. Generating the motion expectation based on the trainer's situation makes the accuracy of user similarity calculation further improved. Finally, the feasibility of this paper's similarity measurement model and recommendation method in trainer health management is measured by analyzing the performance of this paper's similarity measurement model and recommendation method, as well as the recommendation effect of this paper's system in the recommendation of actual dance movement training programs.

2. Personalized dance movement training program recommendation

2.1. User-based collaborative filtering

The main idea of UB-CF is based on the assumption that users who rate some items similarly rate other items similarly. That is to say if a user wants to be recommended, he needs to find users similar to him first.The recommendation principle of UB-CF describes the preferences of four users for four outdoor trainings.From users BCD, we find that user D's preferences are most similar to user A's.In addition to outdoor trainings abc, which is user A's favorite, user D prefers outdoor trainings d, and therefore outdoor trainings d is recommended to user A.The recommendation principle of UB-CF is based on the assumption that users with similar ratings for some items also rate other items similarly. CF performs recommendation in three steps:

Step 1: Data collection. Generate a user-item rating matrix based on the user's historical review information, in addition to user ratings can also be the user browsing history, attention behavior, favorites list, and clicks, etc. When collecting data, the data need to be processed by noise reduction and normalization operations.

Step 2: Finding nearest neighbors. After getting the rating matrix containing the target user, the similarity between the target user and other users is calculated according to the similarity methods, and then the similar K users are taken or the δ -threshold nearest neighbor is taken. The similarity methods are (1) Jaccard coefficient [24]; (2) cosine similarity; (3) correlation similarity (Pearson correlation coefficient); and (4) modified cosine similarity.

1) Jaccard coefficient:

$$sim(u,v)=\frac{|N(u)\cap N(v)|}{|N(u)\cup N(v)|} \tag{1}$$

Or:

$$sim(u,v)=\frac{|N(u)\cap N(v)|}{\sqrt{|N(u)||N(v)|}} \tag{2}$$

Jaccard is used to calculate the similarity of interest using items that have ever had positive feedback, and $N(u)$ represents the set of items that have ever had positive feedback.

2) Cosine similarity:

$$sim(u,v)=\cos(\vec{u},\vec{v})=\frac{\vec{u}\vec{v}}{\|\vec{u}\|\times\|\vec{v}\|} \tag{3}$$

Where: $\vec{u}$ and $\vec{v}$ are the rating vectors of users u and v.

3) Relevant similarity:

$$sim(u,v)=\frac{\sum_{c\in I_{uv}}(R_{uc}-\overline{R_u})(R_{vc}-\overline{R_v})}{\sqrt{\sum_{c\in I_{uv}}(R_{uc}-\overline{R_u})^2\sum_{c\in I_{uv}}(R_{vc}-\overline{R_v})^2}} \tag{4}$$

where: I_{uv} is the item for which users u and v have ratings together, $\overline{R}_u$ and $\overline{R}_v$ are the average ratings of users u and v, c is the item's rated item, and R_{uc} is user u's rating of item item c.

4) Corrected cosine similarity:

$$sim(u,v)=\frac{\sum_{c\in I_{uv}}(R_{uc}-\overline{R_u})(R_{vc}-\overline{R_v})}{\sqrt{\sum_{c\in I_{uv}}(R_{uc}-\overline{R_u})^2\sum_{c\in I_v}(R_{vc}-\overline{R_v})^2}} \tag{5}$$

Corrected cosine similarity compensates for the defects of cosine similarity with different user rating scales, and the symbols have the same meaning as the above formula.

Step 3: Generate recommendation. By step 2, the set of similar users or the set of nearest neighbors of the target user can be obtained, which is denoted by SN_u. The rating of item i by user u on the SN_u-set is P_{ui}, and P_{ui} is calculated as follows:

$$P_{ui}=\overline{R_u}+\frac{\sum_{n\in SN_a} sim(u,n)\cdot(R_{ni}-\overline{R_n})}{\sum_{n\in SN_a}|sim(u,n)|} \tag{6}$$

Where: $sim(u,n)$ denotes the similarity of users u and n, and the other symbols have the same meaning as in the above equation.

After calculating the set of ratings for the items, the set of ratings is sorted from high to low to generate the Top-N ranking, and the best result is recommended to the target user.

2.2. Ontology similarity based training program recommendation approach

2.2.1. Trainer ontology modeling. In order to ensure the personalization and effectiveness of the training program, it must be tailored to the situation of each individual, that is, the so-called "different for each person, the right medicine". Therefore, this chapter combines the relevant knowledge of the dance domain to construct a trainer model for the domain ontology based on the trainer's characteristics. The model can effectively reflect the characteristics and needs of different trainers, which provides important support for the development of personalized training programs.

The dance user model includes the user's basic physical characteristics model and the user's rating matrix model for the program. The user basic physical characteristics model includes the user's basic attribute information and interests. Here the user keywords are extracted, and each keyword is a basic information of the user, and the basic information of the user is age, gender, BMI, and interested dance training category, etc. The user model representation is shown as follows:

$$\overrightarrow{U_u}=\{(k_u^1,w_u^1),(k_u^2,w_u^2),(k_u^3,w_u^3),\cdots,(k_u^n,w_u^n)\} \tag{7}$$

where $\overrightarrow{U_u}$ denotes the feature vector of user u, k_u^n denotes the n th keyword of user u, and w_u^n denotes the weight of the n th keyword of user u.

The user rating matrix model for the item represents the user's liking, or evaluation rating, of the dance training they are interested in. The user's rating level of a dance program contains access, like, share, and favorite. The rating representation is implicitly obtained and expresses the user's preference for the recommended dance training through the user's interface actions.

2.2.2. Reasoning about the core parameters of the training program. In the model, after modeling the user information data, the core parameters of the training scheme will be reasoned through the Jena inference engine, and the reasoning process is shown in Figure 1. Firstly, through the construction of the ontology model, the user information data will be integrated into a unified user ontology file to facilitate the subsequent reasoning process. Second, a series of predicate-atom statements are combined with the domain expertise of the training program to form a pervasive rule file. These rule files are based on domain knowledge and describe the relationships and constraints between different training scenarios, which can help the system understand and infer the user's training needs and health status. Finally, using the Jena inference engine, the system combines the received user ontology files and rule files to obtain the core parameters of the training scheme corresponding to the current user by means of rule-based inference.

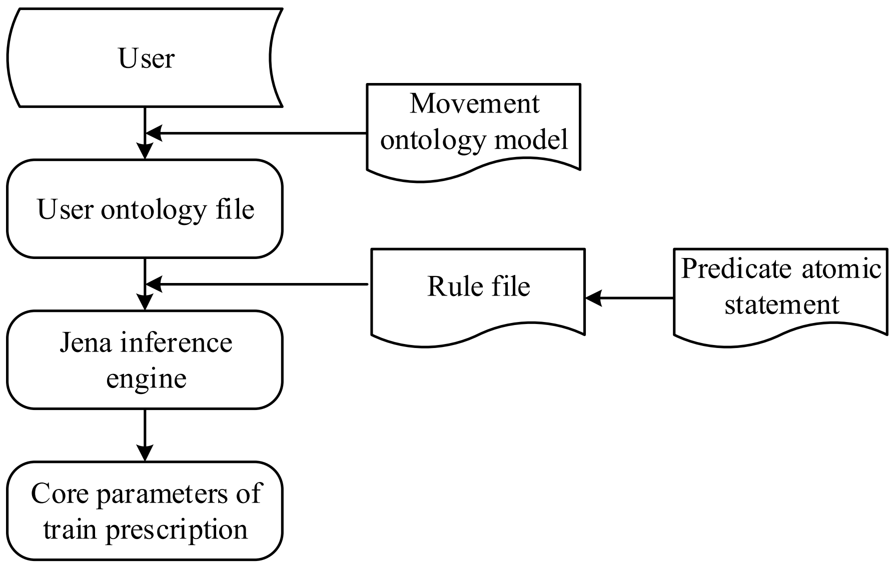

Fig. 1. Core parametric reasoning

The constructed user ontology belongs to the data layer, which is mainly used to describe the user's specific resource information. Ontology reasoning methods can help us to better understand and utilize domain knowledge so as to improve the system's ability to understand and infer the user's needs, thus enabling smarter and personalized services.

In this chapter, the Jena engine is used to build a set of inference rules to better understand the relationship between trainers and their attributes. The Jena rule engine uses a formal rule language, Semantic Web Rule Language (SWRL) [25], which is developed on the basis of the web ontology language OWL, which has a powerful ontology relationship expressive ability to describe the trainer's features and behaviors in a more precise and systematic way.

2.3. User similarity calculation

2.3.1. Similarity calculation based on personal information. In traditional collaborative filtering methods, the same similarity metric is usually used to calculate the similarity of all users, which has some limitations. Because the user's feature variables may include multiple types, and the similarity metrics required for different types of variables are different, the use of a uniform metric may lead to a decrease in the quality of the final recommendation results. In order to solve this problem, this chapter calculates the similarity according to the different variable types in user information separately.

For numerical variable attributes, this chapter uses Euclidean distance to calculate the similarity between them. For numerical variables, they can be regarded as positions on the numerical axis, and the Euclidean distance quantifies the degree of difference between these two positions. Its calculation formula is shown in equation (8).

$$sim_O(u,v)=\sqrt{(u-v)^2} \tag{8}$$

For the training ability variable attributes, this chapter uses cosine similarity to calculate the similarity. Cosine similarity focuses on the direction of vectors without considering their lengths, and it is more suitable for this feature as it ignores the scaling of vectors and focuses more on the directional differences between attributes when calculating similarity. By adopting cosine similarity to calculate the similarity of the attributes of the training ability variables, we are able to more accurately measure the degree of similarity between trainers in terms of training ability. The calculation formula is shown below.

$$sim_C(u,v)=\frac{\sum r_{u_j}\times r_{v_j}}{\sqrt{\sum r_{u_j}^2}\times\sqrt{\sum r_{v_j}^2}} \tag{9}$$

where r_{uj} on r_{vj} are the ratings of target user u and user v for training ability j, respectively.

For categorical variable attributes, such as gender, body size, and training goal, this chapter uses the Hamming distance to calculate the similarity between them. It is able to visually quantify the difference between two categorical variable attributes independent of the string length. Its calculation formula is shown below:

$$sim_H(u,v)=\sum_i d_i \tag{10}$$

2.3.2. Similarity calculation based on training expectations. In the trainer model, the training expectation set contains the core parameters required for users to implement the training program, and the difference of users' expectations for training directly affects the training intensity, time, and frequency required for them to perform training. Therefore, when calculating user similarity, in addition to considering the similarity of personal information attributes, we also need to calculate the similarity of users' training expectations.

In order to achieve this goal, this chapter adopts the core parameters of the training scheme instead of the training expectation for similarity calculation. The similarity calculation formula for training expectations is shown below.

$$sim_{exp}(u,v)=\frac{\sum r_{u_j}\times r_{v_j}}{\sqrt{\sum {r_{u_j}}^2}\times\sqrt{\sum {r_{v_j}}^2}} \tag{11}$$

where r_{uj} and r_{vj} are the values of target user u and user v for training expectation j, respectively.

2.3.3. User similarity calculation based on artificial neural network. Combining user attribute similarity and training expectation similarity yields an overall user ontology similarity, which reflects how similar users are in terms of personal information and training expectations. However, since trainers have a variety of different attribute features and the importance of each user attribute feature can vary for different trainings, how to assign these weights is a key issue. User similarity can be assessed using training effectiveness and satisfaction in the case of training scenarios.

In this chapter, an artificial neural network approach is used to construct a similarity model [26], which can assess the overall degree of similarity between two trainers based on the similarity of the user's numerical-type variables, the similarity of training ability, the similarity of categorization variables, and the similarity of training expectations, as well as the training effectiveness and satisfaction of the corresponding training scenarios. Such a model can consider the user's personal characteristics and training expectations more comprehensively, thus improving the accuracy and usefulness of the recommender system.

In the similarity model, the input of the model is a vector $S(S_1,S_2,\dots,S_i,\dots,S_n)$, S_i represents the similarity value of users u and v on feature i, and the rating deviation P represents the degree of overall deviation from the training effect and satisfaction of the training program case taken into account in a comprehensive manner, which is calculated as shown in equation (12).

$$P = \sqrt{\left((E_u + M_u) - (E_v + M_v)\right)^2} \tag{12}$$

Where, E is the effectiveness score of the training program case and M is the user satisfaction of the training case.

2.3.4. Results of training program recommendations. The calculation results of the overall similarity of the base user can be used to construct a collection of similar trainers of the user. Next, the training solution cases of the top N trainers are selected from this collection of similar trainers and recommended to the target user, thus completing the Top-N recommendation of training solutions. Such a recommendation system can provide users with the most informative and personalized training solution suggestions based on their similarity and preference.

3. Design of personalized dance training recommendation system

Today's training is nothing more than the role of training parts and the combination of training qualities, training parts can be roughly divided into upper limb training, trunk training, lower limb training, etc., training qualities can be divided into speed, strength, endurance, sensitivity, flexibility and so on. Each user's dance training has its own preferred characteristics, in the conduct of a dance training, often do not know and the dance training features similar to what other training programs, which results in the singularity of the dance training, so as to cause the training of the tedious. Furthermore, the characteristics of the dance training that the user participates in over a long period of time are not constant, and when the user interacts with the dance training platform, his preference characteristics change at any time, so the developed platform has the function of recommending training programs of interest to the user according to the user's change in preference for dance training.

User health management mainly includes heart rate monitoring, training heart rate guidance, exercise time statistics, exercise part statistics, exercise training quality statistics. Among them, heart rate monitoring is used to reflect the pattern of the user's heart rate changes with training time. For sick trainers, the minimum training heart rate, appropriate training heart rate and maximum training heart rate calculated by Karvonen's formula should not be used as the standard, but should be used as a reference for the training heart rate of other users who are similar to the target user. Trainers submit data after each training, the system will be based on the trainer's training time and training program characteristics of the trainer's exercise in each exercise part of the workout times and the number of times each training quality, and statistics on the usual exercise time, and finally displayed in the form of charts, to facilitate the user to make adjustments to the training.

After the trainer understands the training program he is interested in, he can check the nearby venues that are convenient for the training in the system. Each training site has a suitable training program to carry out, the trainer can choose the appropriate location for training according to the characteristics of the training program, and can view the route in the system.

The content displayed in the front desk and the functions it has are summarized in the following points:

1) User login: Users can login through the registered account and password.

2) User registration: new users can verify the account number, password and repeated password, and can be registered if the verification is successful.

3) Change password: In the case of the existence of the account, the user can reset the password to change the password.

4) Necessary information to fill out: for new users, the necessary information is user name, name, age, height, weight, disease status, resting heart rate, etc. Perfect before the next step.
5) Fill in the training interest: under the premise of the necessary information are complete, the user must fill in their own interest in the training characteristics, the training characteristics can be multiple choices.
6) Recommended training display: the system provides trainers with dynamic dance training content of interest through the user's interaction in the system, which mainly includes viewing, liking, forwarding and favoriting.
7) Matching training display: the system provides the user with training features that match the user's interest in order to achieve the diversity of dance training.

Through the analysis and description of the previous paper, this paper identifies the training solution recommendation algorithm based on ontological similarity as the personalized dance training recommendation algorithm in this paper. The framework diagram of its recommendation system is shown in Figure 2.

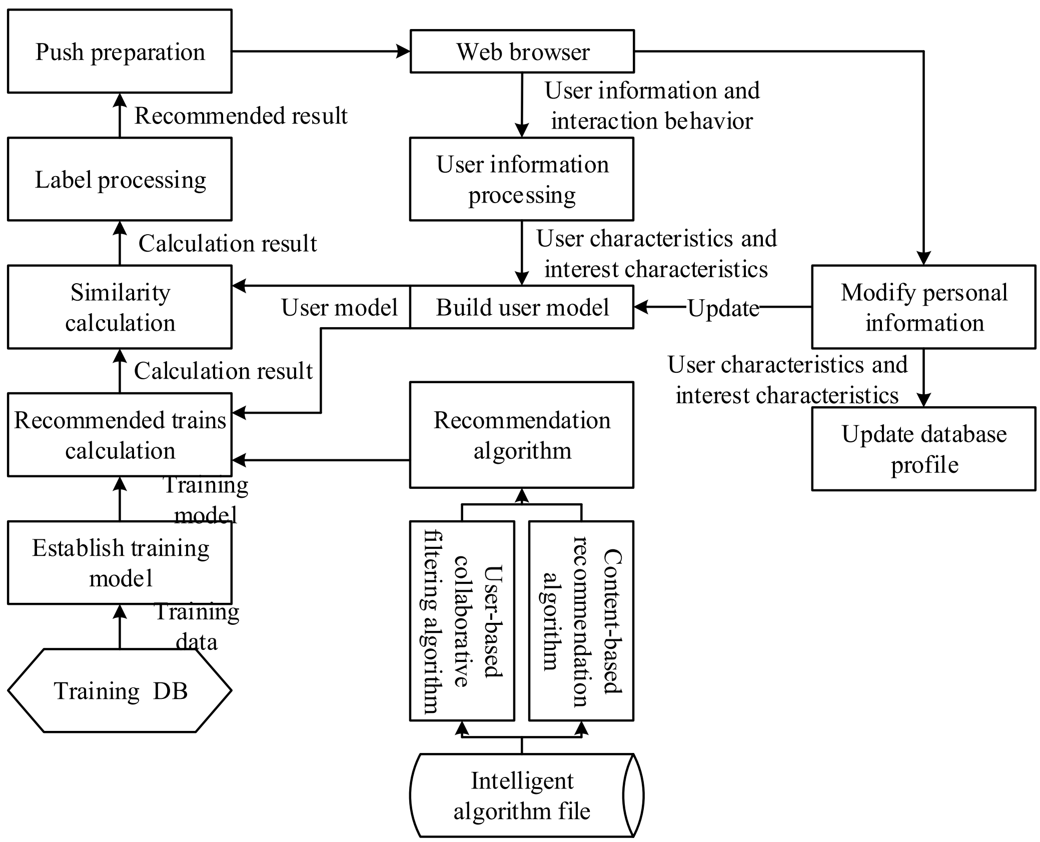

Fig. 2. Recommended system enclosure

4. Personalized dance movement training program recommendation experiments

4.1. Experiments on similarity measures

Due to the low level of informationization of the current training program, complete experimental data cannot be provided. For this reason, the data used in this experiment are simulation data under various training conditions, which are completed under the guidance of two teachers of the training program of the School of Dance, and are mainly used to test the feasibility of the model algorithm. The simulation data used in the experiment contains 50,000 pieces of trainer information data and 50,000 pieces of training case data of each trainer under different training program parameters. Among them, the trainer information mainly includes date of birth, gender, height, weight, waist circumference, chest circumference, hip circumference, body type, muscular endurance, cardiorespiratory capacity, training intensity expectation, training time expectation, training frequency expectation, training history, and training effect preference, etc. The training case data mainly includes training program, training intensity, training time, training frequency, contraindicated diseases, precautions, average completion degree, effect rating, satisfaction rating, overall evaluation and other data.

In this paper, 80% of the data in the experimental dataset is selected as the training set of the neural network, 10% of the data is the validation set, and 10% of the data is the test set. After processing the data in the training set, a total of 130,000 network training samples were obtained, and the hidden layer of the network was finally set as 4 layers after the tuning parameter, and the activation function was ReLU function. In order to verify the effectiveness of this paper's similarity calculation method in similarity discrimination, firstly, 100 trainers are randomly selected in the test set, and the similarity between the current trainer and other trainers in the test set is calculated using this paper's similarity calculation method and the Mahalanobis distance, respectively, and then two similarity measure models are used to construct the similar trainer sets of the 100 trainers, respectively, in which, the storage of the trainers in each set order is determined by the similarity, and the higher the similarity, the more forward the storage.

Finally, the simulation program is used to calculate the mean value of the deviation of the overall effect between each trainer and the first k trainers in its own similar set under the same training conditions, where the smaller the mean value of the deviation indicates the better the screening effect of similar trainers. Figures 3-Figure 5 show the overall effect deviation of 100 random trainers under different similarity metric model screening when the value of k is 3, 10 and 50, respectively. The horizontal coordinate in the figure is the ith trainer among 100 trainers, and the vertical coordinate is the overall effect deviation value of the ith trainer. Whether the similarity calculation method in this paper is at the k value of 3, 10 or 50, the mean value of the overall effect deviation is smaller than the mean value of the deviation calculated by the Mahalanobis distance, which shows that the similarity calculation method in this paper has a better effect of similar trainer screening.

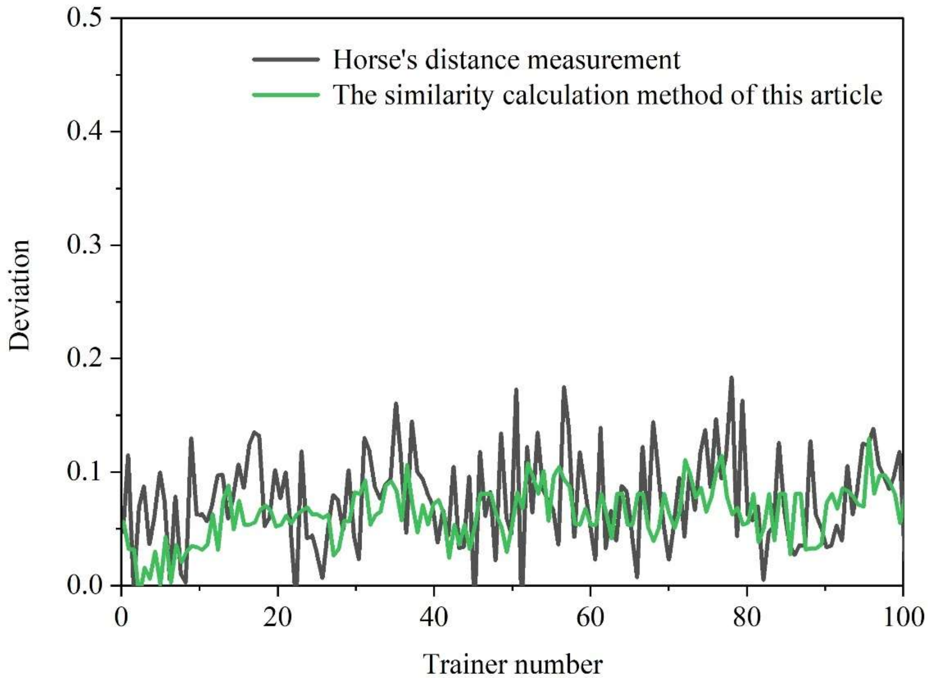

Fig. 3. The overall effect of the k is 3

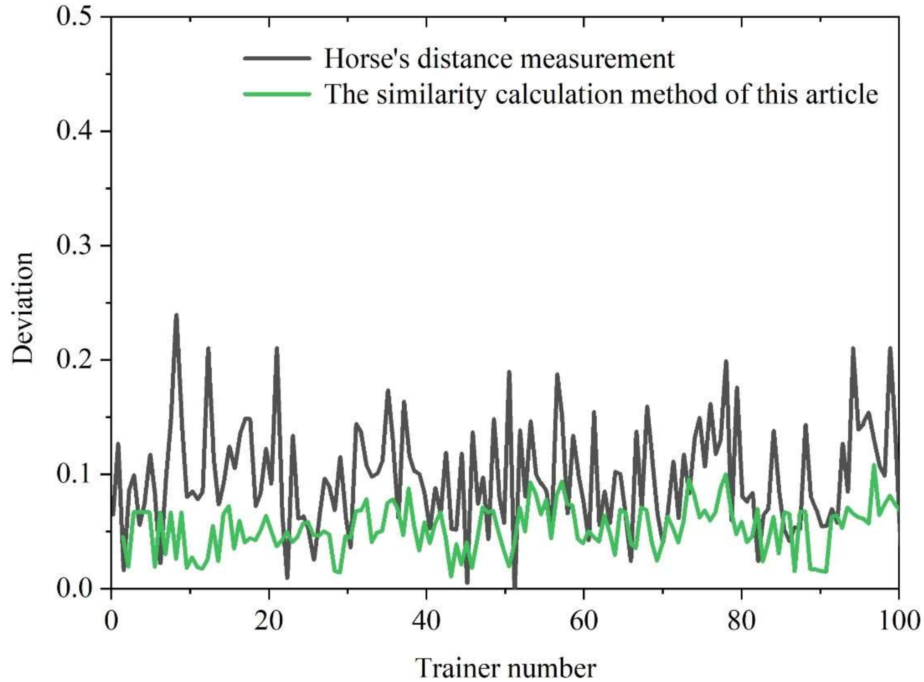

Fig. 4. The overall effect of the k is 10

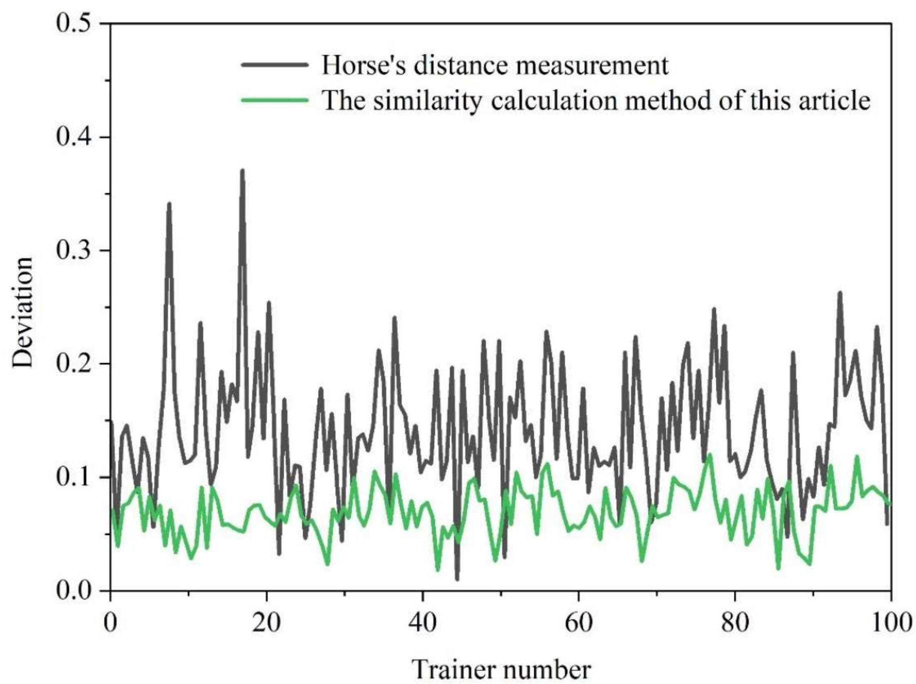

Fig. 5. The overall effect of the k is 50

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), both of which are used to judge the accuracy of the prediction results by calculating the deviation between the predicted results and the true results. In this paper, MAE and RMSE are used to test the accuracy of the network similarity model similarity metric, the smaller the deviation of the calculation of the training results under the same training parameters, the better the accuracy, i.e., the higher the quality of the model algorithm.The MAE and RMSE are calculated as shown in Eqs. (13) and (14).

$$MAE = \frac{\sum_{j=1}^{N} \left| p_{u,j} - R_{u,j} \right|}{N} \tag{13}$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N} \left(P_{u,j} - R_{u,j} \right)^2}{N}} \tag{14}$$

Where N is the number of people in the dataset involved in the similarity calculation, $P_{u,j}$ denotes the mean value of the effect produced by similar trainers of trainer j under the current training parameters, and $R_{u,j}$ denotes the true effect produced by trainer j under the current training parameters. Table 1 gives the MAE and RMSE values of the training effects of 100 random trainers screened by different similarity metric algorithms when the value of K is 3, 10 and 50. From the experimental results, it can be seen that with the same number of K nearest neighbors, the measure of trainer similarity by the network similarity model has better accuracy and higher stability than that of the Mahalanobis distance, and when k=3, the MAE of the network similarity model is only 0.038.

Table 1. The MAE values and RMSE values of different similar metrics

Model	Index	k=3	k=10	k=50
This model	MAE	0.038	0.043	0.062
	RMSE	0.044	0.051	0.068
Horse's distance measurement	MAE	0.065	0.078	0.126
	RMSE	0.069	0.085	0.138

4.2. Experiments on Parameter Recommendation for Training Programs

Since the main application scenarios of current recommendation algorithms are mostly in recommending videos, news, commodities, etc., and the recommendations are specific entities, the direct recommendation of entities is generally used, without changing the information of entities. At present, the most commonly used recommendation method is cooperation-based recommendation, i.e., looking for user groups with similar interests and then recommending the information of entities with high interest in the group. According to this recommendation method, the training program direct recommendation is to find the similar group of the current trainer, and then recommend the effective program information within the group to the current trainer. In this paper, 200 trainers in the test set are randomly selected, and the parameter fusion recommendation approach based on ontology similarity fusion computation and the direct recommendation approach based on cooperation are utilized to recommend the training scheme parameters for these 200 trainers respectively, and the scheme effect grades under the two recommendation approaches are obtained using the scheme effect simulation procedure. Figure 6 shows the 200 trainers' effect ratings under different recommendation algorithms, and Figure 7 shows the average effect ratings produced by the 200 trainers.

From the experimental results, it can be seen that the overall effect of the computational recommendation approach using similarity fusion is better than that of the cooperative direct recommendation based approach in terms of training program recommendation. More importantly, the effect stability of the similarity fusion computational recommendation is better, and the fluctuation range of the effect level is 3-4.5, which can effectively ensure that the effect of the recommended training program will not be too bad, while the cooperation-based direct recommendation is susceptible to the influence of noisy case data, and the stability of the effect is poorer. Training program recommendation on the stability of the recommended effect of the higher requirements, the reason is that the other scenes recommended by the user can determine the advantages and disadvantages and recommend the effect of the user's own influence is not great, but the training program recommended by the user is generally unable to distinguish between the advantages and disadvantages of the training program, and due to the program recommended the effect of the inspection of the cycle is longer, resulting in the recommendation of the effect of the user's influence is greater. Therefore, it is very important to ensure the stability of the training program recommendation. Experimental results show that the similarity fusion recommendation method used in this paper has better overall effect and stability compared to the direct recommendation method.

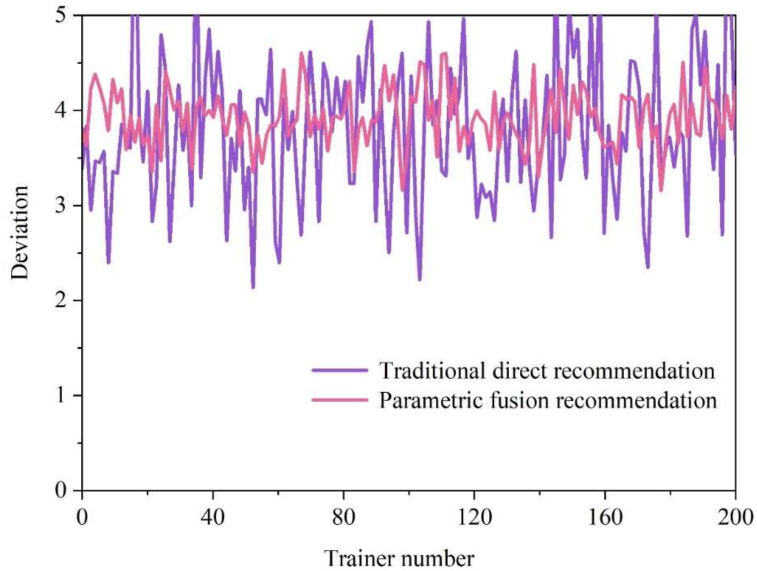

Fig. 6. Comparison of the effects of 200 trainers

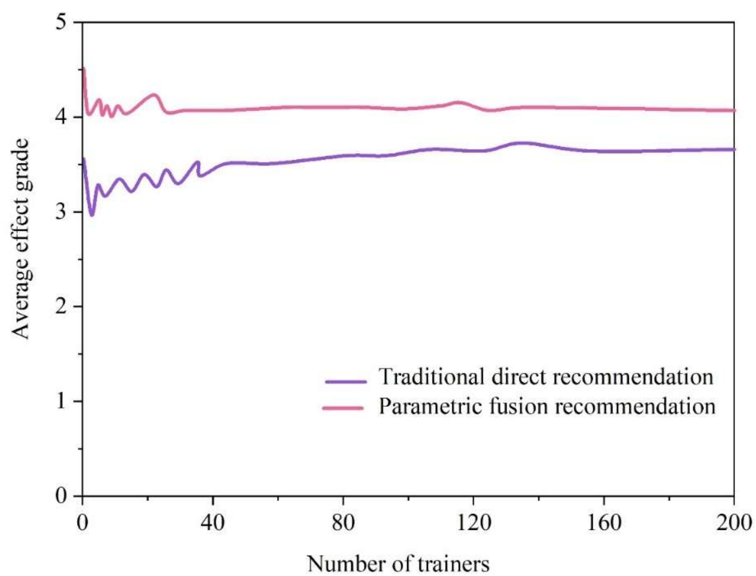

Fig. 7. The average effect level of the trainers

5. Application of personalized dance movement training program recommendation system

To verify the feasibility of the personalized dance movement training program recommendation system to recommend appropriate dance movement training programs as a way to promote trainer health management, this study was based on the monitoring and analysis of the health literacy of students at a dance arts college in City A. Sophomore students were randomly selected from within the boundaries of this college in City A. The study was conducted to determine the health literacy of the students. There were a total of 450 students in this grade, and these students were categorized into populations using the College Training Health Promotion Classification System. Since the dance skills test referenced Skills Standard Level 1, the dance skills categorization consisted of only two categories, Level 0 and Level 1, for a total of 40 categories. In order to achieve the goal of an average of 85 points in the Health Literacy Index in 2035 in City A, this study prioritized the application of a portion of students at the tail end of the Health Literacy Index. Through screening, 10% of students at the tail end of the health literacy index were selected as the survey and test subjects, totaling 40, and they were evenly divided into two groups, and the experiment of daily dance training for college students was conducted on this group of students. In order to verify the reliability of the questionnaire, after 8 weeks, the same personnel conducted another training survey on these students, the experimental group used the traditional training methods, and the experimental group used the personalized dance movement training program recommendation system proposed in this paper to carry out dance training.

The training guidance supported by the personalized scientific guidance system had a greater improvement on the students' physical fitness level scores, and the effect of the system on the students' physical fitness level scores is shown in Table 2. Among them, the weight, BMI and sitting forward bend scores were most significantly improved, and there was a significant difference ($P<0.01$). Lung capacity performance was improved by 491.64 ml and there was significant difference ($P<0.05$). Seated forward body flexion represents hip flexibility and is closely related to the coherence and aesthetics of dance movements of dance trainers. Overweight and obese students have limited hip joint activities due to the accumulation of fat in their bodies, which is not conducive to dance performances, and is also prone to injuries in long-term dance training. The personalized scientific guidance in this paper can significantly reduce the BMI value of students and significantly improve the flexibility of students' joints. Overall, the dance movement training guidance program supported by the personalized scientific dance movement training guidance system achieves the "right medicine". At the same time, the system's monitoring and feedback caused students to be alerted to their dance movement training, thus constantly urging them to carry out dance training. Note: Before and after the experiment, there are significant differences *$P<0.05$, **$P<0.01$.

Table 2. System improves the physical level of students

	Before the experiment (n=20)	After the experiment (n=20)
Height (cm)	166.89±5.71	167.14±5.36
Weight (kg)	64.25±14.55	59.37±14.90**
BMI	27.43±2.41	25.12±1.04**
Lung activity (ml)	4008.07±200.21	4499.71±546.86*
Predisposition (cm)	3.01±4.45	6.59±5.44**

The training guidance supported by the personalized scientific guidance system improves the completion time of students' dance skills such as splitting, lower back, splitting and kicking the back leg significantly, and there is a significant difference in all of them ($P<0.01$), and the effect of improving the completion success rate of the four movements is significant, especially the completion success rate of the kicking the back leg is improved by 65.39%, and the effect of the system on the enhancement of the students' dance skills is as shown in Table 3 shows. The improvement of each technique is mainly due to the feedback and optimization of students' dance skills by teachers with the support of the personalized scientific guidance system, and the feedback is the most influential factor on the learning of training skills besides practice, and the generalization and differentiation process of training skills learning is to establish correct training skills through internal or external feedback. Personalized scientific guidance system can not only correct students' wrong movements and improve the success rate of technical completion, but also help students recognize their own technical deficiencies, mobilize students' motivation to practice, and improve dance skill performance.

Table 3. System effect on student dance skills

	Before the experiment (n=20)	After the experiment (n=20)
Split leg(s)	2.58±0.64	1.48±0.19**
Success rate/%	40.11	89.75**
Lower back(s)	3.97±1.12	2.07±1.35**
Success rate/%	35.67	88.43**
Split fork(s)	5.45±3.74	3.19±1.20**
Success rate/%	49.26	91.53**
Kick back(s)	2.72±1.62	1.02±0.62**
Success rate/%	26.28	91.67**

The effect of the system on the enhancement of students' health knowledge, health awareness and health behavior is shown in Table 4. It is worth noting that this study found that the personalized dance movement training program recommendation system did not have a significant effect on the enhancement of students' health knowledge and health awareness ($P>0.05$), but had a significant increase in student subjects' health behaviors (medium- and high-intensity training time) ($P<0.01$). Health knowledge contains knowledge of healthy nutrition, health care, safety and other knowledge, and its improvement needs to be taught and explained through the corresponding knowledge, relying on the training of scientific guidance can not significantly improve the overall performance of health knowledge. Health awareness is the awareness of participating in health activities on one's own, which can be continuously enhanced during training. 8 weeks of personalized training scientific guidance can briefly improve students' health behaviors by increasing their daily medium- and high-intensity training time, but to significantly improve students' health awareness and health knowledge, more training cycles are needed and more time is needed to grant students with knowledge related to health, so that not only do students have good health awareness and knowledge of health during dance training, but also students have good health awareness and knowledge of health during dance training, so that students have good health awareness and knowledge of health during dance training. So that students not only have good health awareness and health knowledge during dance training, but also have good health literacy in their daily life and study.

Table 4. System improves the students' health related dimensions

	Before the experiment (n=20)	After the experiment (n=20)
Health awareness	88.46±13.15	91.04±10.46
Health knowledge	79.49±11.12	83.01±11.55
Health behavior	25.67±6.14	37.79±5.45**

6. Conclusion

This paper explores a personalized training program recommendation method for dance movements based on the ontology method, and designs and implements a personalized dance movement training program recommendation system based on this method.

1) The effectiveness of this paper's similarity measurement method is verified and analyzed through experiments, and the Mars distance calculation method is adopted as the comparison algorithm of this paper. The mean value of deviation of the overall effect of the similarity calculation method in this paper is smaller than the mean value of deviation under the Mahalanobis distance calculation, and the MAE of the similarity calculation model in this paper is only 0.038 when k=3. It shows that the similarity calculation method in this paper has a better screening effect, and the recommendation

method designed in this paper is better than the traditional recommendation method in terms of its overall performance and stability. It provides theoretical support for the design of personalized training program recommendation system for dance movement.

2) Through the design of the personalized dance training program recommendation system in this paper, the system is applied to the students of dance academy. In order to better verify the role of this paper's system on students' health management, 10% of the students at the tail end were selected to carry out the accurate delivery of scientific dance training programs. The personalized recommendation system of this paper has achieved the “tailor-made teaching”, and the system significantly improved the students' physical fitness level, dance skill performance effect, and increased the success rate of kicking the back leg to 91.67%. However, its effect on students' health knowledge and health awareness is not significant, suggesting that teachers should strengthen the teaching and explanation of students' corresponding knowledge.

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