Research Article

Development and Utilization of Aesthetic Education Resources Using Collaborative Filtering Model

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In students’ education, other educational methods cannot take the place of aesthetic education. This study investigates the creation and use of aesthetic education resources and develops a recommendation model for these resources based on the CF algorithm. The conventional CF algorithm is also enhanced by this study. One by one, the solutions are presented with a focus on the traditional CF algorithm’s cold start and data sparseness issues. Additionally, the system’s requirements, business process, and functional structure are examined in the section on system design. The front-end diagnostic test, the background instructional resource management system, and the recommendation of instructional resources are all realized in the realization section.

According to the experimental findings, this algorithm’s 95.8% recommendation accuracy is 5.87% higher than the user-based recommendation algorithm and 6.03% higher than the item-based recommendation algorithm. The outcomes demonstrate the accuracy and dependability of this algorithm. It can suggest appropriate resources for aesthetic education, fostering the beneficial and healthy growth of students’ aesthetic education.

1. Introduction

The pursuit, evaluation, appreciation, and creation of beautiful things are all activities that fall under the umbrella of aesthetics. In order to promote quality education and students’ overall development, aesthetic education is indispensable [1]. Artistic language and all of its functions are the foundation of aesthetic appreciation. Art appreciation requires aesthetic perception and emotions. In order to appreciate and produce works of art based on an understanding and mastery of the artistic language and basic knowledge, it is necessary for students to master the artistic language and knowledge [2]. We want to impart this aesthetic education through the arts. According to philosophy, aesthetic education aims to mold people’s entire minds and is the pursuit of “unity.” The establishment of people’s conscious awareness of the aesthetic way of spiritual life is given a lot of focus in aesthetic education in order to induce a state of trance in the limited life of the educated object and thereby significantly raises people’s emotional levels [3]. Many gaps in earlier aesthetic education are now apparent in light of the brand-new backdrop of contemporary aesthetic culture. The teaching of aesthetics in schools is frequently limited to the dissemination of aesthetic knowledge, ignoring the development of students’ aesthetic interests, which has issues like singular form and ineffective methods. The issue of how to modify one’s own strategies, objectives, plans, and methods currently confronts aesthetic education. The aesthetic education of today should develop into a big, broad form of education [4]. Additionally, some college students’ lack of aesthetic knowledge and impure aesthetic taste is a result of a lack of aesthetic direction and guidance. The fast-food culture of the media is pervasive today, and consumption has replaced aesthetics. People are becoming more and more devoid of aesthetic connotation because they have not accumulated, refined, or thought deeply enough. As a result, promoting correct aesthetic principles in general and establishing correct artistic aesthetic standards are both tasks of cultural quality education in schools.

The development of other traditional industries has been accelerated by the internet’s ongoing development [5]. It is crucial to effectively combine the value logic of the education
sector with the operation logic of the internet sector because cross-border education is also quietly taking place. Modern education now includes a significant amount of digital learning. In addition to providing for the growing demand for educational resources, the emergence of various platforms for those resources has also altered how people access those resources. It is very simple for people to gather and obtain resources with the aid of the internet’s robust information resources, strong search engines, and quick transmission means [6]. The number of students using the internet is rapidly increasing, and users download and post educational materials there. The availability of educational resources grows exponentially in such a relatively unrestricted environment, leading to “information overload” [7]. People are simultaneously finding it more and more challenging to quickly and accurately locate the information they require. Therefore, recommendation technology was created and demonstrated strong vitality in order to assist people in finding information appropriate for themselves from massive data. There are many different recommended algorithms, but each algorithm has unique benefits, drawbacks, and restrictions. By examining the scoring data, the CF (collaborative filtering) recommendation algorithm identifies this user’s similar user groups and then recommends to the user the top N items from similar user groups with the highest scores, thereby achieving the goal of personalized recommendation [8]. Currently, it is the recommendation technology that is used the most in personalized recommendation systems. However, the two main issues that prevent the further promotion of the CF recommendation algorithm are the cold-start problem and the data sparsity problem. The answer to this query will present pertinent solutions to deal with these two issues. This model can effectively recommend appropriate resources for aesthetic education because the resources it suggests are effective and precise. The innovations of this study are as follows:

1. In the aspect of algorithm, this study deeply studies the principle of the CF algorithm, analyzes its shortcomings, and improves and optimizes it. In this study, the latest learning resource list, popular learning resource list, and user-resource tag matching are introduced to solve the cold-start problem in the CF algorithm. At the same time, the user downloading matrix and the user browsing matrix are introduced to assist the user scoring matrix to solve the data sparseness problem in the CF algorithm. The results show that this algorithm has certain accuracy and reliability. It can provide some technical support for the field of aesthetic teaching.

2. In terms of functions, this study applies the improved CF algorithm to various recommendation functions, and designs and implements download recommendation, rating recommendation, personalized retrieval, and e-mail push functions. The use of the system and the recommendation effect are in the form of a questionnaire. The results show that 94.8% of users are satisfied with the resources recommended by this system. About 95.1% of users are satisfied with the experience of using this system.

2. Related Work

On the one hand, it is overwhelming to see how quickly society and the economy are developing. Strengthening aesthetic education is particularly important because students are often lost in aesthetic values and frequently exhibit aesthetic flaws that ignore and distort beauty. On the other hand, the “internet + education” model has altered people’s learning styles as a result of the ongoing development of network technology. Recommendation systems were created as a result of the proliferation of online learning resources. The use of personalized recommendation technology has significantly grown outside of China in recent years. In China, the technology is still in its infancy, so it is not ideal. After some time of use, some fields have a very developed application of recommendation systems, and the feedback has been positive. The recommendation system can be broken down into e-commerce recommendations, film and video recommendations, music recommendations, social recommendations, news reading recommendations, e-mail recommendations, and recommendations for educational resources based on the application fields it is used in. In the field of education, some researchers have currently used the advised technology and have produced some research findings.

Tuomi et al. proposed that aesthetic education has a unique significance for the spiritual realm of sublimated people. Its direction and value lie in the great effect on the ultimate goal of the whole education, that is, to realize the all-round development of the educational objects [9]. Scanlon et al. proposed that when schools carry out aesthetic education, they should adhere to the combination of on-campus and off-campus to form a three-dimensional aesthetic education network [10]. Murphy P et al. proposed that contemporary aesthetic education should aim at cultivating a new type of cultural character, including the shaping of values, the improvement of personality realm, the development of spiritual personality, and the cultivation of interesting styles [11]. On the basis of fully understanding the importance of using museum resources for the aesthetic education of college students, Santos et al. took the practice of aesthetic education with a museum resource as an example and explored the aesthetic education connotation of museum resources, and expounded some thoughts on the use of museum resources to implement aesthetic education for college students [12]. Iddings D S et al. believe that artistic aesthetic is a creative activity. With the help of the imagination, association, and emotion of recreation, students move into the realm of art, forming the unity of students’ thoughts and works of art; finally, they create a vivid artistic aesthetic image in their minds [13].

Tabuenca B et al. designed and implemented a resource personalized recommendation system [14] by improving the formation method of the nearest-neighbor user set in the traditional user-based CF recommendation algorithm for
recommendating learning resources that meet the real ability level of users. Combined with the specific recommendation object of learning resources, Nitschke H analyzed the current mainstream recommendation algorithms and decided to use the CF algorithm to optimize the push information. At the same time, considering the current cross-platform learning situation of internet learners, the personalized recommendation system for learning resources is designed and developed to support PC, mobile phone, and PAD [15]. Minsky A conducts research on users of online teaching platforms and analyzes the characteristics of this particular group. Then, combined with the item characteristics of instructional resources, a specific recommendation process is designed; the similarity algorithm used in the recommendation process is improved; and a hybrid CF personalized recommendation algorithm based on users and items is proposed [16]. Vagt C examines and promotes in-depth related theoretical research by designing and developing a sample program of a personalized learning resource recommendation system and implementing and continuously testing and maintaining the system [17]. Pappas I O et al. applied the fusion algorithm CB-ItemCF to the educational resource item recommendation system [18]. It not only takes into account the similarity of the content of the questions but also measures the difficulty of a question according to the number of wrong questions. Finally, according to the questions that the students did wrong, the questions of the same difficulty and similar content are recommended. By analyzing the characteristics of educational resources, Walton K studies the general architecture of recommender systems and the related theories and technologies involved. Drawing on current research results, a recommender system based on educational resources is designed and implemented [19]. The system adopts a four-layer architecture system, which are the user UI layer, recommendation layer, offline layer, and data layer from top to bottom.

This study summarizes the benefits and drawbacks of various recommendation methods and suggests a CF algorithm for the creation and use of aesthetic education resources based on an in-depth discussion and analysis of relevant literature. An improved fusion method is proposed in this study with the aim of addressing the issues with the traditional CF algorithm, such as items, cold start of users, and low recommendation accuracy. The learners’ personality traits and learning style traits are simultaneously added to the CF recommendation algorithm in accordance with the characteristics of the educational resource recommendation system. The simulation results demonstrate that this method increases the prediction score’s accuracy and that the recommended resources are better suited to users’ requirements, ultimately increasing users’ satisfaction.

3. Methodology

3.1. Contemporary Aesthetic Culture and Aesthetic Education. Aesthetic education generates its own sense of beauty through the object of beauty, and reconstructs people’s perception, thinking, and moral value orientation. In this way, the proper relationship between individuals and nature and social groups can be effectively established, can appreciate the meaning and interest of life from this relationship, and can consciously use social needs to restrict, standardize, and guide their all-round development [20]. There is an important difference between contemporary aesthetic culture and previous cultural forms. It has been brought into the orbit of economic operation to a great extent, obeying the market power and becoming a kind of consumption culture. Nowadays, due to the continuous progress of economy and society, people are overwhelmed, and college students are lost in aesthetic values. The mass media’s fast-food culture overflows, and aesthetic becomes consumption. People do not have enough accumulation, tempering, and reflection, and they are increasingly short of aesthetic connotation. Aesthetic education is based on moral education, intellectual education, and physical education, and involves a wide range of fields such as life, history, society, and nature. A person must have a broad knowledge background and a certain understanding ability, in order to form the concept of beauty, have a beautiful feeling for works of art, and accumulate beautiful experience. Due to the generalization tendency of contemporary aesthetic culture, today’s aesthetic education must form corresponding new concepts. It should not stick to the traditional definition, but go to a broader cultural field, and greatly expand its functional limits and scope, thus becoming a broad form of education, and a big form of education.

Aesthetic activities foster the true impact of aesthetic education. The cultivation of the educated’s proper aesthetic outlook and aesthetic ability is part of aesthetic education, which is a comprehensive education. The end result of this systematic project is that educated people can consciously create their own spiritual world in accordance with the law of beauty and discover, appreciate, and create beauty. A new cultural character is what modern aesthetic education aims to foster. A cultural character is made up of a variety of elements, including values, personality, spirituality, interesting fashion, and so forth. We can organize students to leave campus and look for, dig up, and experience beauty in the vast ocean of society in order to enhance their ability to appreciate and create aesthetics, particularly the discovery and feeling of social beauty. For instance, frequent trips to museums are a good way to further one’s aesthetic education outside of the classroom. Aesthetic education must begin with the development and practice of artistic aesthetic perception in order for the subject to continually form artistic aesthetic associations, arouse the emotions of aesthetic people, and resonate with artistic works, and on this basis, increase the individual’s aesthetic creativity. In a broad sense, this kind of creation encompasses not only all kinds of inventions and discoveries but also aesthetic-related thought processes. We must ask the educated to assess and direct their own lives using the standard of beauty in order to carry out aesthetic education and establish a civilized lifestyle. Aesthetic education must work closely with cognitive education and ethical education if it is to accomplish the anticipated goal of enhancing educators’ spiritual realm. In essence, the development of people’s spirituality is the
As a kind of personality education and development education, aesthetic education also has its natural advantages in teaching form. It is not only restriction, instruction, and indoctrination, but also guidance, inspiration, and persuasion. It does not impose some pre-established values and norms on others, but implements certain aesthetic principles in the process of generating the value system, so that people can develop and perfect their personality in the self-construction of spirit. We should take aesthetic education of art as the breakthrough of cultural quality education, make use of the communication of art itself and its advantages in developing people's personalities and activating people's thinking, and make use of the advantages that art is more easily recognized and accepted by students compared with literature, history and philosophy education, so that we can more effectively carry out cultural quality education of college students and improve the quality of cultivating talents. Aesthetic education emphasizes “unity of knowledge and action.” The improvement of students' aesthetic ability, and the cultivation and beautification of their spiritual realm should not only be completed in aesthetic practice, but also be tested in aesthetic practice, which should have a positive impact on society. Aesthetic education plays an irreplaceable role in promoting the promotion of personality. Its purpose is not to teach people the ability to make a living, but to help them explore and find a way of development and advancement.

3.2. Personalized Recommendation and CF Algorithm.

The CF recommendation algorithm differs from other recommendation algorithms [21]; in that, it can be applied to unstructured complex objects, such as video, audio, pictures, and compressed packages. Among them, the most famous ones are the CF algorithm based on users and the CF algorithm based on projects. Its core idea is that what users need are the items that users like him need. The CF technology is based on the interest direction of neighboring users, using other users’ preferences for resource items to obtain the similarity of users, or predicting a user’s evaluation of a resource through the common likes and dislikes of similar users. According to these data, the system can make personalized recommendations with high accuracy. The core idea of the user-based CF algorithm is to recommend items that are of interest to users who are similar to users. Therefore, the key steps of this algorithm are the construction of a user-item rating matrix describing user behavior rating data and the calculation of similarity between users. The steps are as follows: construction of prediction score matrix → search of similar items → generation of prediction results and recommendations. This algorithm is suitable for scenes where the number of items is far less than the number of users, and the number and similarity of items are relatively stable. Because the similarity between items is fixed, in the collaborative recommendation algorithm based on items, the similarity between items can be calculated offline. This can save the calculation time and solve the real-time problem of the system to some extent. However, whether it is the similarity filtering algorithm based on users or the CF algorithm based on items, when the score data are not large enough, the similarity calculation results between users and items are often not accurate enough, thus affecting the personalized recommendation results. Figure 1 shows the functional requirements and modeling process of the aesthetic education resource recommendation system.

The biggest difference between CF and content-based recommendation algorithm is that it makes full use of the feedback behavior information of all users and generally uses the user-item scoring matrix as the data source. When the CF recommendation algorithm is applied to a specific personalized recommendation service, it does not need to pay attention to the type, attribute, and structure of system items. It has the characteristics of a wide application range of recommended items, accurate recommendation, and high recommendation efficiency. This is the advantage of this algorithm, which also makes the CF algorithm get unanimous praise. The data of recommendation results calculated by the CF algorithm come from the scoring records of all users on the system. This algorithm has two shortcomings. First of all, the number of users is constantly changing, and its scalability is relatively poor; second, it also has the problem of data sparseness, that is, there are so few valid scoring data in the user-item scoring matrix that it is impossible to find a neighboring user for the target user. In practice, with the increasing number of users and projects, the user-project scoring matrix will become more and more sparse.

3.3. Recommendation of Aesthetic Education Resources Based on CF Algorithm.

In the first stage, user modeling is mainly to acquire knowledge related to maintaining user interests, user needs, or habits. The result of user modeling is to generate a user model that represents the user’s unique background knowledge or interests and needs. The core functions of the system are mainly divided into two parts. The first part is the sharing function of learning resources, which mainly includes users uploading, browsing, commenting, grading, downloading, and deleting learning resources; the second part is the personalized recommendation of learning resources. The database is the storage layer and persistence layer of the whole system. It includes database user information, learning style information, resource information, and information of learners operating learning resources. As the recommended object of this system, educational resources need to express their characteristics in some way, and establish links with other resources and user interest models. This study mainly adopts the vector space model. The component interaction and recommendation process of the system are shown in Figure 2.

The fundamental component of a recommendation system is the recommendation algorithm, which also serves as a crucial base for a variety of recommendation functions. Given that the foundation of this system is educational resources, it is necessary to design the corresponding
The recommendation algorithm in accordance with the traits and current state of educational resources. Sharing of learning resources, the system’s fundamental building block, offers data support for tailored recommendations of learning resources and is employed in CF calculations. The goal of data collection is to gather details about user preferences, characteristics, and activities. It offers a vital information source for user modeling. Users must voluntarily submit information about their interests and preferences during explicit collection. Users’ manual participation is not necessary when using an implicit method. However, under the user’s typical activities, the system automatically completes the task. It is advised for online real-time use that after gathering the user’s behavior data, offline processing pre-processes the data, analyses the user’s behavior log, and trains the user’s feature model. Interactivity, security,
stability, and scalability are all given top priority in this study’s system design. The data model developed in this study not only keeps track of the fundamental data about the learning resources, such as the name of the resources, a detailed description of the resources, the storage address of the resources, the category, type, and degree of difficulty of the resources, but it also keeps track of how the learners use the resources, such as the quantity of learners who download the resources, the keywords used for the resources, and the resource uploaders. In order to create a final user model with structured representation, one must interpret and reason about the data that have been gathered, remove noise from it, form useful knowledge about the user’s interests, and format this knowledge. The user-project scoring matrix is constructed as shown in the following formula:

\[ R(m, n) = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix} \]

(1)

Among them, the number of rows \( m \) represents the number of users; the number of columns \( n \) represents the number of items; and the value \( r_{ij} \) in the matrix represents the rating data of the item \( n \) by the user \( m \). For the calculation methods of similar users, most of the current personalized recommendation systems mainly use the following: cosine similarity, modified cosine similarity, and correlation similarity. The formula for calculating cosine similarity is as follows:

\[ \text{Sim}(u, v) = \cos(\vec{u}, \vec{v}) = \frac{\vec{u} \cdot \vec{v}}{|\vec{u}||\vec{v}|} \]

(2)

The modified cosine similarity is as follows:

\[ \text{Sim}(u, v) = \frac{\sum_{I_{ui} \in I_{ui}} (r_{ui} - \bar{r}_u)(r_{vj} - \bar{r}_v)}{\sqrt{\sum_{I_{ui} \in I_{ui}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{I_{vi} \in I_{vi}} (r_{vj} - \bar{r}_v)^2}} \]

(3)

The similarity is as follows:

\[ \text{Sim}(u, v) = \frac{\sum_{I_{ui} \in I_{ui}} (r_{ui} - \bar{r}_u)(r_{vj} - \bar{r}_v)}{\sqrt{\sum_{I_{ui} \in I_{ui}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{I_{vi} \in I_{vi}} (r_{vj} - \bar{r}_v)^2}} \]

(4)

Among them, \( \vec{u} \) and \( \vec{v} \), respectively, represent the vector values of user \( u \) and user \( v \) in the space vector model; the item set represented by \( I_{ui} \) represents those items that both user \( u \) and user \( v \) have rated; \( \bar{r}_u \) and \( \bar{r}_v \) represent the average project scores of user \( u \) and user \( v \), respectively; \( r_{ui} \) and \( r_{vj} \), respectively, represent the rating values of user \( u \) and user \( v \) to item \( i \); \( I_u \) and \( I_v \), respectively, represent the score set of user \( u \) and user \( v \) to the item. The similarity of similar users based on explicit feedback data can be calculated by the following formula: Pearson’s correlation coefficient method:

\[ \text{Pearson}(a, b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}} \]

(5)

Among them, \( \text{Pearson}(a, b) \) is recorded as the similarity between user \( a \) and user \( b \) calculated by Pearson’s correlation coefficient method. The symbol \( \bar{r}_a \) represents the average rating of the user \( a \). \( r_{a,p} \) and \( r_{b,p} \) represent user \( a \) and user \( b \)’s rating of an item’s \( p \), respectively. Euclidean distance is as follows:

\[ \text{Distance}(a, b) = \sqrt{\sum_{p \in P} (r_{a,p} - r_{b,p})^2} \]

(6)

Among them, \( \text{Distance}(a, b) \) is recorded as the similarity between user \( a \) and user \( b \) obtained by using the Euclidean distance calculation method. We assume the union of itemsets rated by target user \( u \) and user \( i \), respectively:

\[ I_{ui} = I_u \cup I_i \]

(7)

For item \( k \) that is not rated by user \( u \) in \( I_{ui} \), the rating of user \( u \) for item \( k \) is predicted by the similar itemset \( SI_k \) of item \( k \) as follows:

\[ P_{uk} = \frac{\sum_{m \in SI_k} \text{Sim}(k, n) \cdot (R_{m,n} - \bar{r}_n)}{\sum_{m \in SI_k} \text{Sim}(k, n)} \]

(8)

The above method is looped to fill the predicted value into the scoring matrix, so that users \( u \) and \( i \) have scores for all items in the item set \( I_{ui} \). Using Pearson’s similarity algorithm, the similarity between target user \( u \) and \( i \) is as follows:

\[ \text{Sim}(u, i) = \frac{\sum_{k \in I_{uk}} (R_{ik} - \bar{R}_i) \cdot (R_{uk} - \bar{R}_u)}{\sqrt{\sum_{k \in I_{uk}} (R_{ik} - \bar{R}_i)^2} \sqrt{\sum_{k \in I_{uk}} (R_{uk} - \bar{R}_u)^2}} \]

(9)

We search on the entire user set and select the top \( N \) users with the greatest similarity to user \( u \) as the nearest-neighbor set \( N_u \) of user \( u \). The predicted score \( P_{ui,j} \) of the target user \( u \) for the item \( j \) is as follows:

\[ P_{ui,j} = \frac{\sum_{n \in N_u} \text{Sim}(u, n) \cdot (R_{n,j} - \bar{R}_n)}{\sum_{n \in N_u} \text{Sim}(u, n)} \]

(10)

Among them, \( \bar{R}_u \) and \( \bar{R}_n \) represent the average rating of the item by user \( u \) and user \( n \), respectively; \( \text{Sim}(u, n) \) represents the similarity between user \( u \) and user \( n \). After calculating the user’s \( u \)’s preference for different items, the \( N \) items that have a higher preference and are not in the user’s self-rated item set are selected as the top \( N \) recommendation set.

The MVC architecture divides the system into three basic parts: model, view, and controller. The architecture consists of data layer, business logic layer, and display layer. The clear hierarchy of the system can make it easier to understand the system architecture in the development process and improve the development efficiency. As a platform for sharing educational resources, this system provides teachers and students with rich instructional resources. The user
information is provided by the users of the system when they register, so as to obtain the basic information of the users that has a great influence on the resources recommended by the recommendation system. The personal center of the system includes user information, announcement, latest announcement, and all announcements. The resource center includes user resources, system resources, personalized recommendation, user comments, resource review, the latest resource ranking, and hot resource ranking. The classification of aesthetic instructional resources includes the following: media materials, question bank, test paper materials, cases, literature, FAQ, resource catalogue index, and online courses.

4. Result Analysis and Discussion

In order to verify the effectiveness of the improved CF recommendation algorithm proposed in this study, relevant experiments are designed. Compared with the traditional user-based CF recommendation algorithm and project-based recommendation algorithm, this algorithm proves its superiority. The machine hardware configuration used in the experiment is Intel Core 2 Dual-Core Processor, 512M memory, and 1T hard disk. The operating system is Windows; the programming language is Java; and the database system is MySQL. In this experiment, MAE (mean absolute error), which is the most widely used and intuitive statistical accuracy measurement method, is adopted as the evaluation standard. According to the deviation between the predicted user’s rating of the project and the actual user’s rating, the accuracy of the three algorithms is analyzed. The calculation formula of MAE is as follows:

\[ MAE = \frac{1}{n} \sum_{i=1}^{n} |p_i - q_i| \]  \hspace{1cm} (11)

Among them, \( p_i \) is the predicted rating value of the item, and \( q_i \) is the actual rating value of the user. The smaller the calculated MAE, the higher the accuracy of the recommendation algorithm. The MAE test results of different algorithms are shown in Table 1.

In the experiment, the sparse level of the dataset is also considered, which is defined as the percentage of items in the user-item scoring matrix that are not scored. The data sparsity of this experiment is 0.92. The higher the score, the higher the user’s preference for the resource. We compare and analyze different recommendation algorithms. The running time comparison of different algorithms is shown in Figure 3.

The number of nearest neighbors has a great influence on the accuracy of recommendation. Generally, the more the nearest neighbors assigned to users, the higher the accuracy of recommendation, and the lower the MAE. In this experiment, the nearest neighbors are 10 to 50, and the difference between the neighbors is 5. The experimental results are shown in Figure 4.

It can be seen that the MAE of the improved CF recommendation algorithm is lower than that of the traditional CF recommendation algorithm. This result shows that the accuracy of the improved CF recommendation algorithm is higher than that of the traditional CF recommendation algorithm under any number of nearest neighbors. The accuracy result of the prediction score is shown in Figure 5.

As a common method of system testing, function testing refers to the user-level testing of functional modules that

| Number of experiments | User-based recommendation algorithm | Item-based recommendation algorithms | This study improves the recommendation algorithm |
|-----------------------|-------------------------------------|--------------------------------------|-----------------------------------------------|
| 1                     | 0.874                               | 0.846                                | 0.653                                         |
| 2                     | 0.841                               | 0.816                                | 0.674                                         |
| 3                     | 0.863                               | 0.759                                | 0.634                                         |
| 4                     | 0.831                               | 0.804                                | 0.607                                         |
| 5                     | 0.817                               | 0.811                                | 0.611                                         |

Figure 3: Comparison of running time of different algorithms.
Figure 4: MAE experimental results.

Figure 5: Prediction scoring accuracy of the algorithm.

Table 2: System function test results.

| Module                              | Functional test                  | System response                                                                 | Test result |
|-------------------------------------|-----------------------------------|---------------------------------------------------------------------------------|-------------|
| Login module                        | Normal login                      | Successfully entered the system                                                 | Pass test   |
| User information module             | User name or password is empty    | System prompt: user name and password do not match                              |             |
|                                    | Modify user information           | If the modified user information does not meet the input requirements, the input box will turn red and an error message will be displayed | Pass test   |
| Learning resource uploading module  | Save user information             | System prompt: information saved successfully                                  | Pass test   |
| Learning resource download module   | Upload learning resources          | System prompt: resource upload successfully                                      | Pass test   |
| Learning resource deletion module   | View the uploaded learning resource information | Display a list of uploaded assets                                               |             |
| Personalized recommendation module  | Download learning resources        | System prompt: download successful                                              | Pass test   |
| module of learning resources        | Delete learning resources          | System prompt: deleted successfully                                              | Pass test   |
|                                    | View recommended learning resources| The system displays the learning resource details’ page                          | Pass test   |
| Exit system                         | Log out                           | Back to landing page                                                            | Pass test   |
have been completed in the system development. In this process, the system is often deployed to the server to run. When testing, testers only pay attention to whether the test results are consistent with the expected results of this function. The system function test results are shown in Table 2.

According to the information in the table, the test results are in line with the expected goals, and the recommendation system based on aesthetic education resources is realized. The use of the system and the recommendation effect are in the form of a questionnaire. The scores of users after using the recommendation system are counted, and the subjective score data of users are shown in Figure 6.

The results show that 94.8% of users are satisfied with the resources recommended by this system. The result is higher than the comparison model. This shows that most users are satisfied with the experience of this system. This is a considerable result. A comparison of recommended accuracy results of different algorithms is shown in Figure 7.

From the comparison results, it can be seen that the recommendation accuracy of this algorithm reaches 95.8%, which is 5.87% higher than that of the user-based recommendation algorithm and 6.03% higher than that of the item-based recommendation algorithm. This result shows that the performance of this algorithm is better. Through experiments in this chapter, it is found that this algorithm has certain accuracy and reliability. In addition, this chapter also tests each functional module and performance of this system, and the test results are in line with the expected goals, thus realizing the recommendation system based on aesthetic education resources. The model studied in this study can recommend suitable resources for aesthetic education, thus promoting the positive and healthy development of students’ aesthetic education.

5. Conclusions

In order to prevent students from being forced to examine their own aesthetic psychology and behavior using uniform standards and patterns, aesthetic education should pay attention to both generality and individuality. The traditional barrier between teachers and students must be broken in order to give students the opportunity to engage in equal communication while experiencing the aesthetic space that teachers and students jointly create during the educational process. The majority of students have an aesthetic desire. Students should be able to directly experience sight and sound as a result of the cultural quality education provided in schools, and an artistic atmosphere should be fostered on campuses. Aesthetic education is a significant way for contemporary college students to unwind from the strain of their demanding academic and social lives. This study builds a recommendation model of resources for aesthetic education on the basis of an in-depth analysis of the CF algorithm and aesthetic education. This model can offer precise and effective resources for aesthetic education, raising students’ level of aesthetic awareness. According to the experimental findings, this algorithm’s 95.8% recommendation accuracy is 5.87% higher than the user-based recommendation algorithm’s and 6.03% higher than the item-based recommendation algorithm. The accuracy and dependability of this algorithm are certain. The performance and function modules of this system are also tested, and the test outcomes are consistent with the anticipated outcomes, realizing the recommendation system based on resources for aesthetic education. It can suggest appropriate resources for aesthetic education, fostering the beneficial and healthy growth of students’ aesthetic education. There are still some issues that need to be resolved, despite the fact that the research in this study clearly produced some positive results. The benefits and drawbacks of real-time updating and timing updating must be carefully weighed in the future research process in order to choose the best updating method for updating and maintaining the model.
Data Availability
The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest
The author declares that he has no conflicts of interest.

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