

Retraction

Retracted: Personalized Recommendation Model of High-Quality Education Resources for College Students Based on Data Mining

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] C. Fang and Q. Lu, "Personalized Recommendation Model of High-Quality Education Resources for College Students Based on Data Mining," *Complexity*, vol. 2021, Article ID 9935973, 11 pages, 2021.

Research Article

Personalized Recommendation Model of High-Quality Education Resources for College Students Based on Data Mining

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With the rapid development of information technology and data science, as well as the innovative concept of “Internet+” education, personalized e-learning has received widespread attention in school education and family education. The development of education informatization has led to a rapid increase in the number of online learning users and an explosion in the number of learning resources, which makes learners face the dilemma of “information overload” and “learning lost” in the learning process. In the personalized learning resource recommendation system, the most critical thing is the construction of the learner model. Currently, most learner models generally have a lack of scientific focus that they have a single method of obtaining dimensions, feature attributes, and low computational complexity. These problems may lead to disagreement between the learner’s learning ability and the difficulty of the recommended learning resources and may lead to the cognitive overload or disorientation of learners in the learning process. The purpose of this paper is to construct a learner model to support the above problems and to strongly support individual learning resources recommendation by learning the resource model which effectively reduces the problem of cold start and sparsity in the recommended process. In this paper, we analyze the behavioral data of learners in the learning process and extract three features of learner’s cognitive ability, knowledge level, and preference for learning of learner model analysis. Among them, the preference model of the learner is constructed using the ontology, and the semantic relation between the knowledge is better understood, and the interest of the student learning is discovered.

1. Introduction

With the in-depth development of education informatization, online education is highly respected by the majority of learners [1]. Online education combines traditional teaching mode with Internet technology, overcoming the drawbacks of traditional education restricted by time, space, and environment and enabling the sharing and reuse of high-quality educational resources on a larger scale [2]. Online learning (e-learning) greatly improves learners’ motivation, helps learners understand knowledge more comprehensively, and improves learning efficiency and learning effectiveness. With the rapid increase of online learning users, learning resources are presented at an explosive rate, making learners face difficulties such as “information overload” and

“learning lost” in the learning process, and learners have to struggle to find the information they really need from the vast sea of learning resources [3]. Therefore, pushing appropriate learning resources for different learners is the focus of personalized learning in the online education environment [4]. Personalized learning emphasizes that the learning process is a process of promoting the full, free, and harmonious development of students in all aspects by adopting appropriate methods, means, contents, and evaluation methods according to their individual characteristics and development potential [5].

The traditional teaching model has many factors that are not conducive to learners’ learning. First, the teaching mode is single [6]. The traditional classroom teaching system regards learners as a whole and adopts the “one-size-fits-all

uniform model” and “duck-fill model,” which is mainly “teacher-centered.” The teacher transmits knowledge and the learners receive it simultaneously. It ignores the differences in learners’ knowledge level, learning ability, and learning preferences in the learning process [7]. It is easy to cause some learners to be less motivated and have a negative attitude to resist learning, which leads to low motivation to learn. Second, learning activities are limited by time and space. Students can only transfer knowledge through teachers during classes. Third, educational resources are unbalanced [8]. There are certain differences in the level of education and teaching in the eastern, central, and western parts of China in terms of teacher strength, geographical differences, teaching resources, and teaching equipment [9]. The emergence of modern education information technology model has transformed the traditional “teacher-centered” model into a “learner-centered” personalized and selective learning model [10]. Teachers are able to teach precisely through learners’ online learning behaviors, learning styles, learning preferences, and other personal characteristics; learners can access resources shared by experts through the Internet, and they can enter a community that suits their learning and collaborate with community partners to learn [11]. The education informatization mode has changed the teaching defects in traditional teaching, reversed the teaching method, and truly realized “teaching according to the material” and “personalized teaching” [12]. In order to promote the further development of education informatization, the Ministry of Education has proposed a new idea, “Internet + Education” in the “13th Five-Year Plan of Education Informatization.” It is hoped that an effective way and method can be found to achieve the goal of education informatization, so that information technology can be fully and widely applied in the field of education [13]. In order to realize the recommendation of personalized resources and the innovative concept of “Internet+” education, personalized recommendation systems have emerged, such as MOOC, Netease Open Class, and Coursera course recommendation, and mobile independent learning class [14].

In mobile independent learning, learners conduct independent learning, collaborative learning, and personalized learning through the learning platform according to their own time and needs [15]. After years of application, the teaching platform stores a large amount of teaching materials and learning resources and uses educational data mining to analyze learners’ learning behaviors, knowledge levels, and learning preferences in the learning process and to discover the defects and risks in the learning process, as shown in Figure 1. In summary, in order to solve the problems of blindness and inappropriate resources in the search for learning resources, the data recorded during the learning process are used rationally to discover learning resources that match students’ own personality characteristics [16]. In this paper, we propose an individual learning resource recommendation model for students and study cross use of multidimensional data. By combining the two, a personalized resource recommendation model that satisfies the learner’s cognitive ability, knowledge level, learning

preference, and learning goals is designed, and the extension and application in the Educational Resource Recommendation application scenario have specific academic values [17]. The construction of the personalized learning resource recommendation model is in line with the characteristics of pedagogy and learners’ learning rules, and the application of this study not only meets learners’ interests and preferences but also helps learners to accomplish their learning goals well and achieve better learning results, which has certain application value [18].

With the development of information technology, a large amount of data is explosively exploited in business, urban transportation, medical field, and biology research field. More and more scholars and researchers are examining these data. And, the online education data mining and application is a new research hot spot in the field of data mining, artificial intelligence, machine learning, complex network recently, and personalized education in high-quality online education environment. This paper takes up the study of personalized learning resource recommendations and learning preferences in an online education environment. In this paper, we analyze the requirements of Individualized Recommendation System for educational resources from the problem of “information overload” by huge educational resources and propose the application of CB-Item CF-SVD++ algorithm to personalized recommendation system of educational resources. The personalized education resource recommendation system includes a resource browsing function. The recommendation system has the functions of recommendation and search for editing, acquiring, and downloading related resources. In addition, it also has the function of inputting educational resource data and the function of data updating.

2. Related Work

David Goldberg first used collaborative filtering in 1992 in a paper entitled “Using collaborative filtering to weave an information tapestry” at the Xerox PARC. The concept of collaborative filtering was first used in a paper entitled “Using collaborative filtering to weave an information tapestry.” Nowadays, most web sites use collaborative filtering algorithms in various aspects; in 1995, Pattie Maes’s lab at MIT successfully commercialized recommendation system technology and founded agent; in the same year, researchers from Carnegie Mellon University and Stanford University jointly presented personalized recommendation at the American Association for Artificial Intelligence (AAAI) [19]. In the same year, researchers from Carnegie Mellon University and Stanford University jointly presented personalized recommendation at the AAAI, and they showed the world personalized recommendation systems, Web Watcher and LIRA, for the first time; it won the 2006 Netflix Million Dollar Award, which reflects the popularity of personalized recommendation system development. Since then, more and more researchers have paid attention to this field, and the research of personalized recommendation technology has been maintained at a high level so far [20]. At present, recommendation systems are widely used in

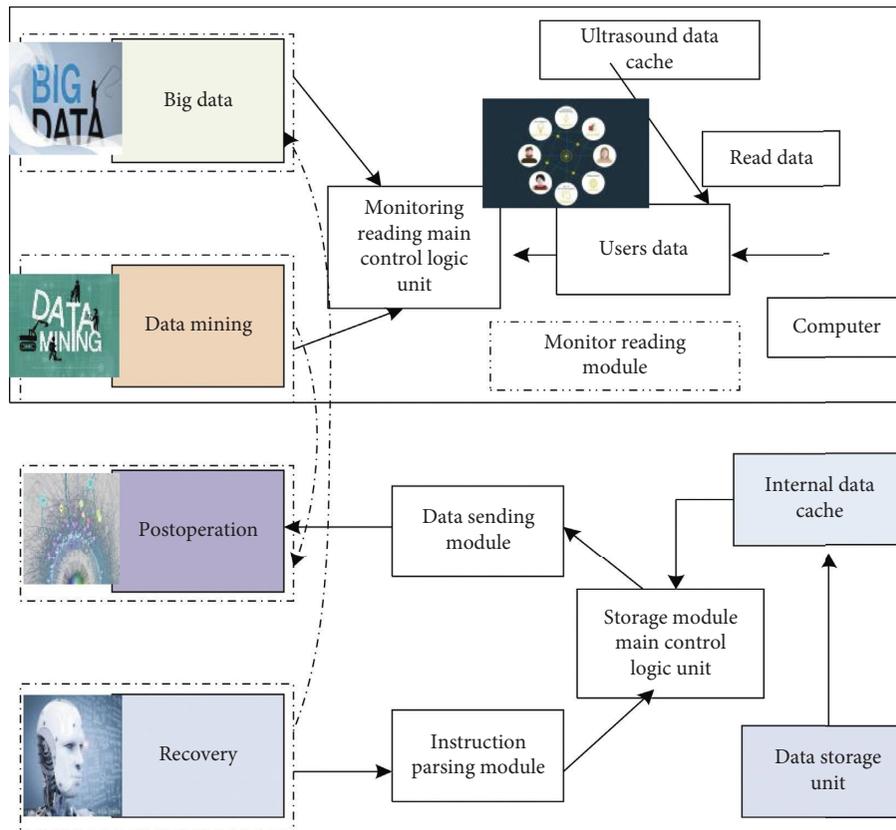


FIGURE 1: Self-directed teaching platform.

e-commerce, movies, music, advertising, news, social networks, and other fields. Especially in the field of e-commerce, it has brought great commercial value. Some famous foreign websites that use recommendation algorithms include Amazon, Netflix, and Hulu. Among them, Amazon makes recommendations for its products to increase the purchase rate of users, which contributes to at least 20% of Amazon's annual revenue. The use of recommendation systems can be seen everywhere on the Amazon website [21].

For example, Amazon's Today's Recommendations module can recommend some new items on the shelves to users based on the current popular products, users' recent purchase records, and browsing records, which can solve the cold start problem based on item recommendations [22–24]. The bundle sales module analyzes the user's purchase behavior through machine learning technology and recommends some items that are often bought together to the user. There are also other products purchased by module, which is a typical application based on item collaborative filtering recommendation algorithm to help users discover items of interest. Netflix is a US-based online movie rental provider. The company offers a large number of DVDs for users to choose from and delivers them for free [25–27].

To reduce the number of DVDs the user changes when the user's hiring rate is increased and the user is not satisfied, Netflix uses the recommendation system to recommend the favorite movies and reduce the number of rentals that are not satisfied and increase the number of rental movies. Since

Netflix is seriously committed to the recommendation system, we have recommended a recommendation engine contest to reward the team that can improve the Netflix recommendation engine in 2006. This event has not only enhanced the accuracy of Netflix's recommendation system but also enhanced the popularity of Netflix and attracted talented people working with Netflix, which is proficient in recommender engine algorithms. The importance of foreign study on the recommendation system is clear. Through accurate personalized recommendations, products are presented to customers so that the user experience is improved and the potential needs for purchase are found and eventually sales increase. In the field of education, the research and application of the recommendation system is not as much as e-commerce but plays a major role in promoting the process of computerization of education. Currently, e-learning that is popular in foreign countries applies many personalized recommendation techniques, the e-learning system intelligently fulfills the individual needs and preferences of the learner and promotes relevant learning resources that meet the learner's characteristics, and personalized learning enables BIS. E front learning, doctor, Moodle, and so on are representative products in this field. In addition, the recommendation technology is widely used in some digital education projects.

Until the end of the 20th century, Resnick et al. took the lead in proposing the definition of personalized recommendation. With the improvement of national

comprehensive strength and the comprehensive entry of technological achievements such as big data, Internet, and artificial intelligence into human life, learners are not satisfied with passive learning in the face of high-speed online learning environment but become active participants in learning, “information overload” is now a serious problem faced by Internet learners, and personalized recommendation systems are a powerful tool to solve this problem and have attracted the attention of many scholars and researchers. Personalized recommendation systems have been successfully applied in many fields such as business, information retrieval, biomedicine, and smart city transportation, such as Amazon book recommendation, eBay, and Netflix movie recommendation.

3. Overall Design and Implementation of Personalized Recommendation System

3.1. Design Objectives. The recommendation system based on the educational resources designed in this paper is based on the rational resource integration scheme and the recommended strategy as a subsystem of the digital publication resource aggregation and delivery service system and personalized customized services to users. Ultimately, it enables teachers and students to obtain educational resources quickly and easily, improves their learning efficiency and resource utilization, and realizes efficient delivery of digital publishing resources for modern education industry, as shown in Figure 2. To meet the above business objectives, the design goals of this system are as follows:

- (1) The system can quickly analyze user behavior and educational resources, build corresponding models, provide efficient recommendation engines, and effectively solve the problem of “cold start” and sparse data.
- (2) The system has good interface interaction, provides rich recommendation functions, and can provide different personalized recommendation services according to different usage scenarios of users.
- (3) The system can efficiently handle high concurrent requests and support concurrent access by a large number of users, and at the same time, it must also have good stability.
- (4) Good scalability is also a factor that must be considered to support the extended recommendation algorithm. This needs to ensure that as the number of users and resources continue to grow, the system can still ensure high performance.

3.2. Demand Analysis. The core of this paper is the recommendation system, so the analysis is focused on the necessary functions related to the recommendation system. Figure 3 shows the functional requirements of the recommendation system based on educational resources. As a result, the basic requirements of the system are as follows:

- (1) Model building and recommendation algorithm requirement educational resources, as the recommendation object of the system, need to represent the characteristic attributes of the resources in some way and to establish links with other resources and user interest models. In this paper, the vector space model approach is mainly used. For this purpose, it is necessary to parse the content of educational resources, which involves the separation of text content and the extraction of topic keywords, construct the feature space vector of resources, classify the resources into topics using the relevant clustering algorithm, and calculate the similarity between individual resources for use in the recommendation process. The recommended algorithm is the core part of the recommended system and is an important basis for implementing various recommendations. Since the system is based on educational resources, it is necessary to design the recommendation algorithm according to the characteristics and actual conditions of educational resources. Furthermore, in the recommendation system, the data spur problem and the “cold start” problem are inevitable. In this paper, we investigate and analyze traditional collaborative filtering in order to effectively reduce the effect on the recommended effect and combine the three algorithms of model-based content-based and item-based collaborative filtering and weighted hybrid reasoning model. Collaborative filtering algorithms cannot be recommended in real time for large amounts of computation in case of big data.

The collaborative filtering algorithm cannot make recommendations to users in real time due to the large amount of computation in the case of big data. The collaborative filtering algorithm based on weighted hybrid recommendation model effectively solves this problem. In the model-based collaborative filtering algorithm, the model is trained with historical data, the average ratings of the rows and columns of the rating matrix are weighted, and the corresponding α and β should be set according to the contribution of the average weighted rating of users and the average weighted rating of items. Three formulas are proposed here, in which the average weighted score of user i is calculated as

$$r_u = \frac{1}{T_{\max}} + \sqrt{\sum_{i=0}^n t_i + T_{\min}}, \quad (1)$$

where K is the total number of user ratings for item i and k is the rating of unrated item i by user k . The average weighted user rating is the sum of the average user rating and the average deviation of the user’s ratings from the average rating of the unrated items. The formula for calculating the average weighted score of item i is as follows:

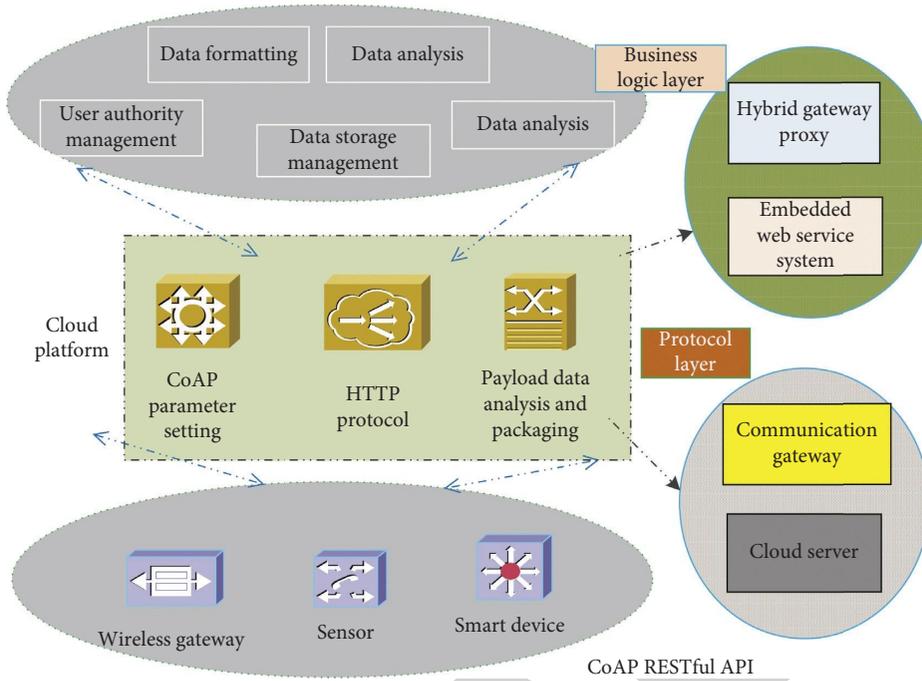


FIGURE 2: Design of personalized recommendation system.

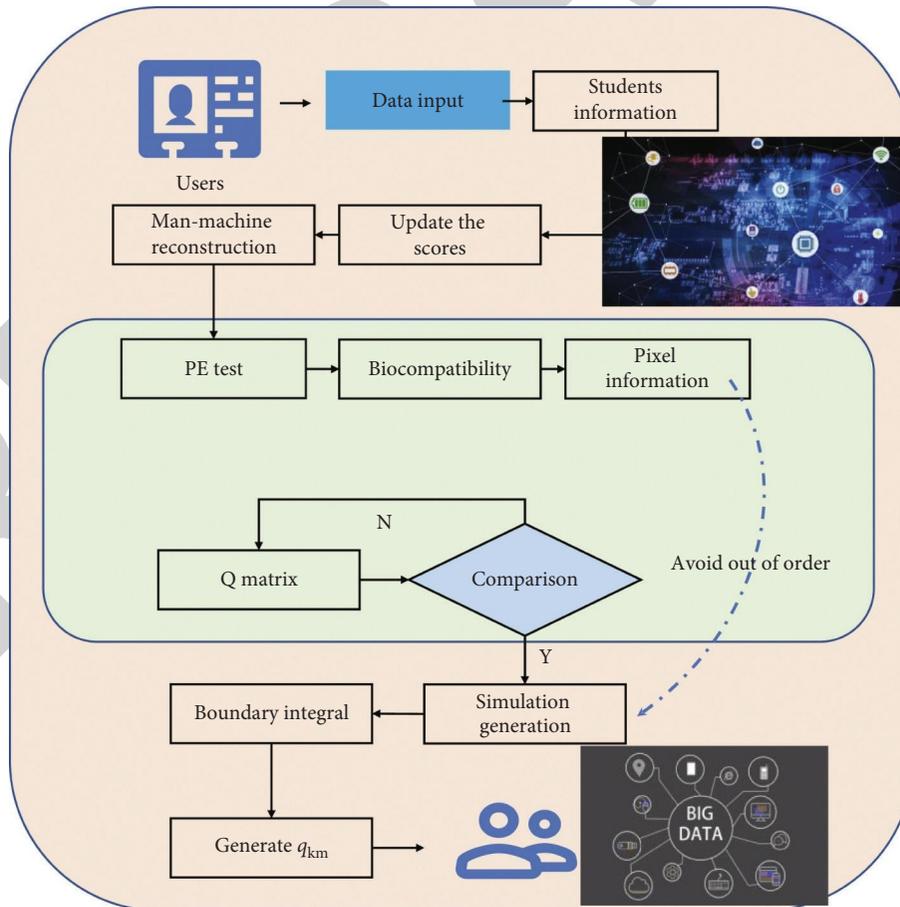


FIGURE 3: Functional requirements of education resource-based recommendation system.

$$r_i = r_u + \frac{\sum_{i=0}^n \sum_{j=0}^n (t_i + T_{\min})_{ij}}{\sqrt{(t_i + T_{\max})_{ij}}}, \quad (2)$$

where Q is the total number of ratings of the item space by user u ; k is the value of the ratings of user u on q . The average weighted rating of the item is the sum of the average rating of the item and the average deviation of the ratings of the unrated item i by each user in the user set from the average rating of the user. The weighted scores are then integrated to obtain the formula

$$r_{n,i} = \alpha r_i + \sum_{j=0}^m \sum_{i=0}^n \text{sir}u(n_i, n_j). \quad (3)$$

This results in an integrated weighted score for the unrated items and after filling the corresponding items, any item in the matrix has a score for items i and j . With the introduction of the contribution determination parameters α and β , the integrated weighted score consists of two parts, the user's subjective score and the objective rated factors of the items, and the contribution of the two in the whole formula is different, because the addition of the determination parameters makes the recommendation results more accurate.

(2) Recommended functional requirements

The recommendation function is a specific application of the recommendation algorithm module. Multiple recommendation algorithms can be applied to the same recommendation function, and the same recommendation algorithm can be applied to multiple recommendation functions. In order to provide rich and better personalized recommendation services to teachers and students, the system will provide the following recommendation functions: recommendation of related resources when users download resources, recommendation based on user ratings, and personalized search services when users search for resources.

(3) User basic functional requirements

The system is divided into two roles: system administrator and general user. The role of general user corresponds to the real application scenario of the majority of teachers and students. Therefore, the system first needs to provide login and registration function as the entrance of users into the system and be able to set the user's grade, subject, interest, and other attributes, which also provides data for building the user model.

This system serves as a sharing platform in terms of educational resources, providing teachers and students with massive and rich teaching resources, and functions such as resource retrieval, online browsing, uploading, and downloading are all necessary. In addition, the resource scoring and commenting functions are very important for the

recommendation system. It not only helps other users to understand a resource but also is an important basis for the recommendation system to analyze the interests of that user and provide personalized services. For the system administrator, it is also an important participant in the system. Its main responsibility is to maintain the system, so this system gives it more management functions, mainly system management, resource management, and user management. The administrator's use of these functions directly or indirectly affects various model construction, mining algorithms, and recommendation strategies and thus the operation of the whole recommendation system.

The basic functional requirements of users are divided into the following functional modules:

(1) Resource browsing function module

After successful login, users can browse all teaching resources and view them in the form of ranking, such as release time, number of downloads, rating, and uploader. They can also search for resources under the category they want to view and retrieve the resources they need by keywords; in addition, they need to visually display detailed information about the resources to users, such as resource title, resource category, resource description, and upload. It is also necessary to display detailed information about the resources to users, such as resource title, resource category, resource description, upload date, number of downloads, uploader name and user type, resource comments and resource score, and other pieces of resource information.

(2) Upload and download function module

Users can upload and download resources, where the resources uploaded by student users will not be released immediately, until the teacher user logs in and enters the resource review, you can see all the resources to be reviewed, the resources will be released if they pass the review, and if they do not pass the review, they will be deleted by the teacher user. When users find the resources they need, they can download them locally for study.

(3) Scoring and commenting function module

When users use the resources, they can give feedback and rating on the advantages and disadvantages of the resources through scoring and comments, so that the excellent resources can be more fully recognized and used and help other users to better locate the resources they need to choose. Through comments, users can also discuss and share problems and learning experiences encountered during the use of the resource for communication and exchange.

(4) Message alert function module

When the resources uploaded by students do not pass the teacher's user review and are deleted, the student users are notified through in-site messages,

so that students can fully grasp the situation of their uploaded resources; when the resources uploaded by users get new comments, the users are also notified through in-site messages, so that the users can understand the evaluation of their uploaded resources by other users and better stimulate the users to improve the quality of their uploaded resources, so as to optimize the whole The purpose of the teaching resource management system is to optimize the whole system.

(5) Home teaching resources recommendation module

When students log in to the system to visit the home page, the recommendation system will calculate a list of teaching resources recommendations to be displayed on the home page based on the current student user's past preferences for teaching resources and the attributes of teaching resources currently in the system to help student users discover teaching resources that may be of interest.

(6) Teaching resources detail page recommendation module

When students log in to the system to access the detailed page of teaching resources, the recommendation system will recommend teaching resources that are similar to the teaching resources they are currently browsing and are likely to be of interest to the current students based on the teaching resources they are currently browsing, their past teaching resource preferences and the attributes of the teaching resources currently in the system.

(7) Resource management function module

Teacher users can edit and delete resources. Editing includes modifying the title, description, and classification of resources and deleting invalid or unneeded resources to make the resource library more standardized and rationalized. Teacher users can dynamically manage the classification of resources, including adding new classifications, modifying classification names, and deleting classification operations. The purpose of updating the resource categories instantly as the resources are diversified is achieved. The operation of deleting categories can delete empty categories, that is, no resources under a category, or delete all resources under a resource category, that is, when a category of resources expires or is needed again, to achieve the purpose of deleting resources in bulk according to the resource category. Teacher users can delete comments, if there are malicious, inaccurate, or worthless comments and delete to achieve the purpose of purifying the site and better help users to quickly and accurately locate resources and find what they need.

(8) System management module

This module is mainly done by the system administrator. For the system administrator, it is also an important participant of the system. Its main

responsibility is to maintain the system; therefore, this system gives it more administrative functions, mainly system administration, resource management, and user management. The administrator's use of these functions directly or indirectly affects various model building, mining algorithms, and recommendation strategies, which in turn affects the operation of the whole recommendation system.

3.3. *System Architecture Design.* The architecture of the recommendation system designed in this paper is divided into three layers: user UI layer, business layer, and data layer. The architecture of the system is shown in Figure 4.

(1) User UI layer

The user UI layer is responsible for the interaction between users and the system, responding to user requests and displaying content results, such as login and registration, information settings, and resource browsing. In addition, this layer also records the user's access to the website. The user's access records include browsing resources, collecting resources, purchasing resources, and commenting resources. These user's behaviors will be recorded in the user behavior log database.

(2) Business layer

This layer mainly implements the core business logic of search recommendation, including the following two modules. The first module is recommendation module. This subsystem mainly analyzes and calculates user information, user behavior, and teaching resource information and establishes a model, uses demographics-based, improved content-based recommendation algorithms, improved item-based collaborative filtering algorithms, and other combinations of recommendation strategies to design adaptive recommendation strategies, and selects different recommendation algorithms for users to recommend resources according to different scenarios. This layer implements the recommendation function of resources and submits the recommendation results to the user UI layer for display. This layer includes two aspects: on the one hand, it uses relevant fusion technology to realize the synthesis of the advantages of different algorithms to complement each other's strengths; on the other hand, it develops some filtering rules from the perspective of product and operation to filter out resources that do not meet the conditions or actual needs. The second module is offline module. The main function of the offline layer is to analyze and process the data in the data layer and provide data support for the recommendation algorithm in the recommendation layer, which mainly includes the following two aspects: initial construction and adjustment of the resource model; analysis of the data by using relevant data mining algorithms.

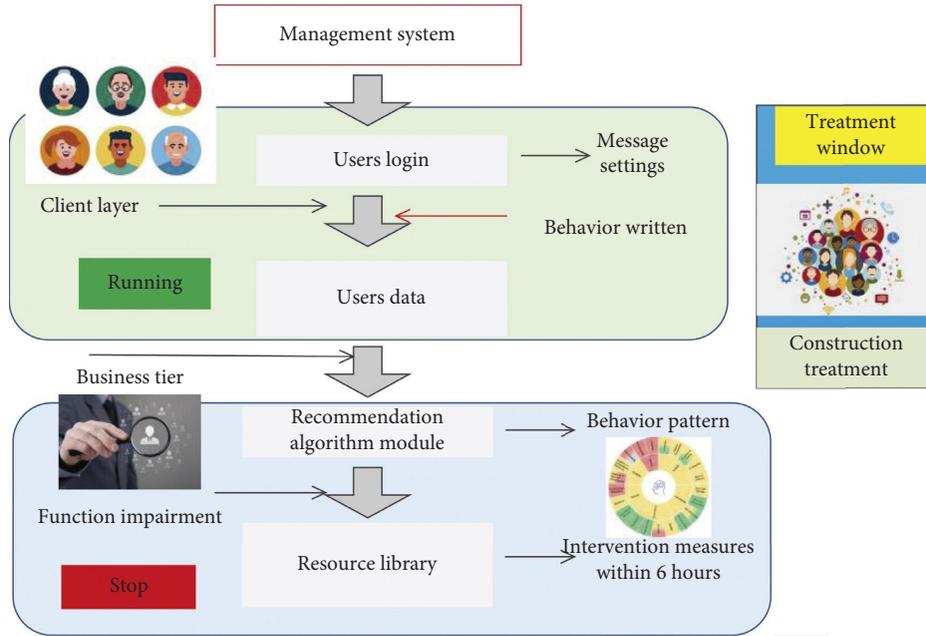


FIGURE 4: Architecture diagram.

(3) Data layer

It provides basic data storage services and does backup and disaster recovery work to ensure safe and reliable data. In accordance with various application requirements, the storage layer is subdivided into a database that stores user information, a database that stores educational resource information, and a log database for storing the behavior of the user. User information database is mainly used to store personal information filled in when users register, including user ID, user name, encrypted login password, user's province, user's county and city, and user's unit, and preference information set by users, including school sections, subjects, grades, and versions that users pay attention to. Resource information database is mainly used for storing various educational resources, such as classroom recordings and other types of resources. User behavior log database is mainly used to store various operation behaviors of users, such as browsing, collecting, purchasing, commenting, and other historical records, which are used to build user preference models in the subsequent stage of analysis, as shown in Figure 5.

4. System Optimization Test

After designing and implementing this personalized recommendation system for teaching resources, the recommendation model needs to be tuned and evaluated, so the evaluation algorithm is needed, and the evaluation test is mainly conducted by offline method in this paper. The evaluation algorithm plays a very important role as a standard for measuring the recommendation effectiveness of the recommendation system. The user evaluation data of

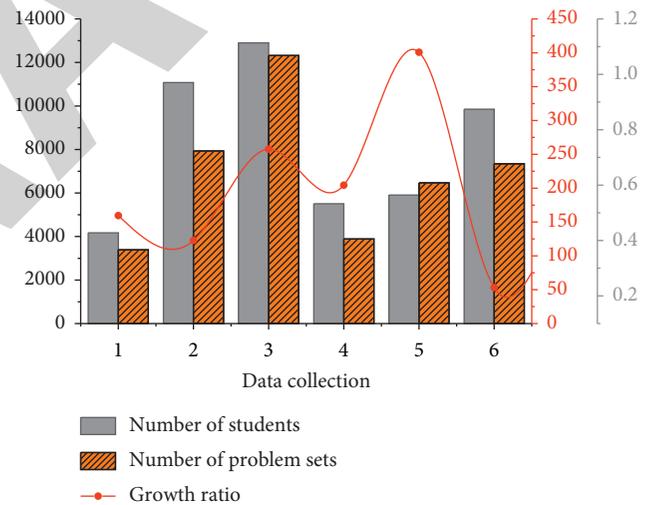


FIGURE 5: Summary of user profile information.

resources can also be obtained from the database of user behaviors such as purchase, collection, and comment and then processed to get the comprehensive rating. In this experiment, more than 500 users with more ratings and the rating data of more than 400 resources by these users are selected according to the user ratings, and these data are filtered to filter out the user ID, resource ID, comprehensive rating, and rating of students. The final rating matrix is obtained by implicitly scoring. In general, the personalized recommendation algorithms are based on open-source datasets such as Movie Lens, which is the oldest recommendation system. It was founded by the Group Lens project group at the School of Computer Science and Engineering at the University of Minnesota as a noncommercial, experimental site for research purposes. Its main function is to

recommend movies of interest to users. In order to make the recommendation algorithm more widely available and to contribute to the development of educational technologies, experiments were conducted on educational data and the correctness of the results was analyzed. In addition, in order to investigate the specificity of educational data, this paper also conducts experiments on the Movie Lens dataset and finally compares the results of the two experiments to analyze the specificity of educational data. In this experiment, the CB-Item CF algorithm, SVD++ algorithm, and CB-Item CF- SVD++ algorithm will be compared, and Figure 6 shows the comparison of the accuracy obtained by different kinds of recommendation algorithms with different K values (number of nearest neighbors).

According to the above figure, when k is 60, the highest accuracy of SVD++ algorithm is 68.51%, while the accuracy of CB-Item CF- SVD++ algorithm in this paper is 72.52%, which is the most accurate recommendation algorithm in this experiment, so it can be seen that the improved algorithm has better performance than the original algorithm. In the following experiments using Movie Lens, the data of Movies Lens are rated in the range of 1–5, and we choose MAE to measure the performance of CB-Item CF algorithm, SVD++ algorithm, and CB-Item CF- SVD++ algorithm on Movies Lens data. Figure 7 shows the performance of these three algorithms for different k values.

As can be seen in Figure 8, the CB-Item CF algorithm performs reasonably well, but the CB-Item CF-SVD++ algorithm used in this paper performs better. Through the above experiments, it can be seen that the algorithm of this paper can make the recommendation results more accurate in the system, and the performance of the improved algorithm has been improved. The CB-item needs to prepare the prestudy lesson plan according to the learners' characteristics and understanding ability and send the prestudy lesson plan to the learners through the mobile independent learning platform, after which learners prestudy according to the teacher's prestudy lesson plan and their own actual situation, while parents also need to take valuable time to pay attention to the learners' learning and to prestudy and supervise them before class.

In the learning platform, learners, teachers, and parents use their mobile devices to communicate and interact with each other, thus influencing each other and achieving their respective purposes, such as teachers complete lesson preparation, lectures, assignments, and class evaluations; learners complete pretesting, pretesting, listening to lectures, taking notes, drawing mind maps, and so on; parents mainly complete supervision and guidance of learners and at the same time get real-time information on learners' school. The parents are mainly responsible for supervising and guiding the learners, as well as obtaining real-time information about the learners' assessment results at school and the situation after contact.

- (1) Before conducting a new lesson, in order to ensure that learners can accept the new knowledge more

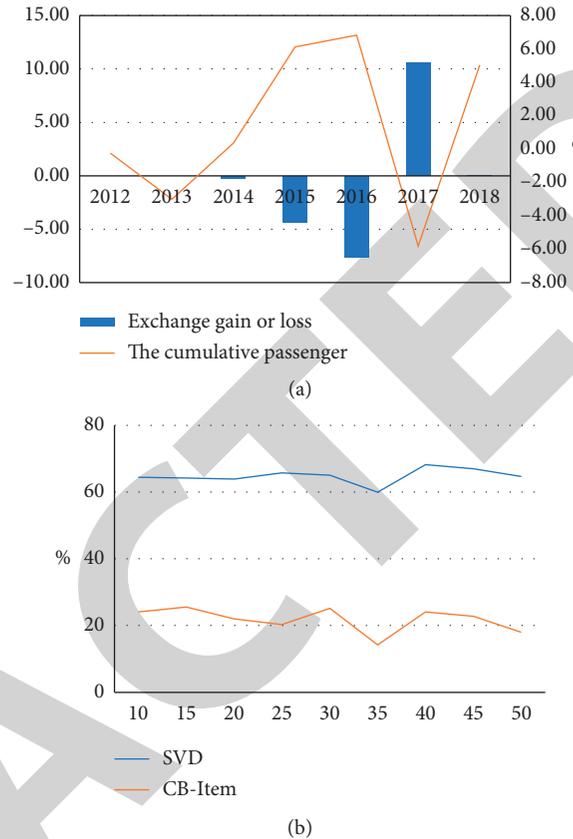


FIGURE 6: Precision values of the three recommendation algorithms for different k values.

quickly, the teacher-learner-parent triad needs to help with the prestudy of the new knowledge.

- (2) In the pretesting stage, a contextual introduction is designed for pretesting introduction according to the teaching content learned in the lesson, and the learners' mastery of the pretesting questions is analyzed. For this situation, parents should also encourage and praise the learners to teach.
- (3) In the stage of explaining the important and difficult points, learners will encounter many important and difficult points through the pretest stage after completing the test questions, because the teacher has not yet taught the learners systematically, and what they have to do in this stage is that the teacher will explain the important and difficult points in detail, and learners should listen carefully and complete the writing of notes according to their questions in this process.
- (4) With postpractice link, in order to test the learners' learning in the classroom, teachers design post-practice questions, learners complete the test questions so as to achieve the role of consolidating knowledge points, and at the same time, parents check the effect of their children's learning through postpractice online.

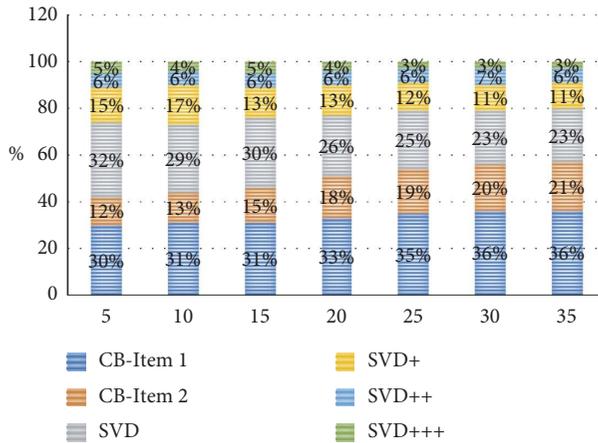


FIGURE 7: Comparison of MAE of three algorithms for different k in MovieLens dataset.

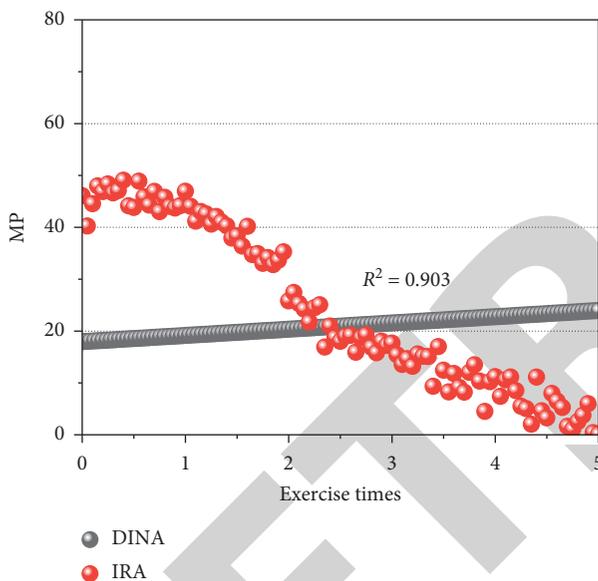


FIGURE 8: Accuracy comparison between different algorithms.

5. Conclusion

With the continuous development of the information age, especially the steady advancement of mobile Internet, people are rapidly entering the era of big data. In contrast to the rapid growth in the amount of information, people have not gained significant changes in the speed of acquiring new knowledge and acquiring new abilities. The personalized recommendation of information is to make the user only need to process the recommended partial information to approximate or exceed the effect that can be produced by processing all the information before. In the process of learning, people's mastery of knowledge will be divided due to various reasons, and in the teaching process, teachers can only adopt the method of unified course arrangement that only takes care of the majority of people due to the limited energy of their lectures and after-class assignments. Therefore, the combination of data mining methods makes it

possible to personalize teaching aids for different students, which has become a hot research topic. As an important part of the education process, the personalized recommendation of exercises is even more important.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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