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Retraction

Retracted: Adaptive Recommendation Method of IoT Apps and Ideological and Political Teaching Resources

Wireless Communications and Mobile Computing

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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] Y. Hu, "Adaptive Recommendation Method of IoT Apps and Ideological and Political Teaching Resources," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5983366, 14 pages, 2022.

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Research Article

Adaptive Recommendation Method of IoT Apps and Ideological and Political Teaching Resources

Yanhua Hu (ID)

School of Marxism, Shenzhen Polytechnic, Shenzhen 518055, China

Correspondence should be addressed to Yanhua Hu; 19402346@masu.edu.cn

In view of the current poor nature of online ideological and political teaching and the deficient impact of the executive teaching resource recommendation, this paper advances the examination on the versatile recommendation technique for online ideological and political teaching resources under the school enterprise cooperation mode, gathers and deals with the ideological and political teaching data in view of the teaching qualities of the school enterprise cooperation mode, and develops the assessment calculation of teaching data the board. At last, through tests, it is affirmed that the versatile recommendation technique for online ideological and political teaching resources under the school enterprise cooperation mode has high practicability and fully meets the research requirements.

1. Introduction

The research on the adaptive recommendation technology of intelligent teaching resources under the school enterprise cooperation mode plays a vital role in the efficient presentation and accurate acquisition of teaching resources. At present, the representative technologies of how to improve the intelligence of resource acquisition at home and abroad mainly include automatic word segmentation, data mining, collaborative filtering, and genetic algorithm [1]. As a key technology and basic work in information processing such as text classification, information retrieval, and information filtering, automatic word segmentation has always been a research hotspot in the field of information retrieval. Relevant scholars have proposed many automatic word segmentation algorithms, which can be roughly summarized as dictionary word segmentation method, statistical word segmentation method, understanding word segmentation method, and combination word segmentation method [2]. Among them, the dictionary word segmentation method is more mature and easy to implement. Due to the complexity and flexibility of natural language and the difficulty of knowledge representation in information resource description, it is often necessary to combine with other technologies

to improve the retrieval accuracy in practical application. In view of the low accuracy and personalized service of the query and feedback results of teaching resources, this paper designs an adaptive recommendation model of teaching resources based on the school enterprise cooperation mode, which makes the model more intelligent, provides personalized services for users, and dynamically adjusts and presents the retrieval content of teaching resources [3]. We investigate the use of artificial intelligence (AI) and Internet of Things (IoT) technologies in ideological and political classroom education and intelligent educational systems based on real-world educational conditions to improve the efficiency of ideology and to build an education in the political classroom.

2. Adaptive Recommendation of Online Ideological and Political Teaching Resources

2.1. Collection and Management of Online Ideological and Political Teaching Resources. During the time spent building recommendation strategies, assuming there is model direction, it will come by two times the outcome with around 50% of the work. Be that as it may, there is no framework model for customized recommendation of learning

resources in the field of education [4]. The customized recommendation procedure for learning resources can be viewed as the particular utilization of the recommendation framework in the field of education and a versatile learning framework. Hence, the general model of the recommendation framework and the general model of the versatile learning framework can give a reference. In any case, the general model of recommendation framework is basically focused on the business field and cannot be completely pertinent to the customized recommendation of learning resources [5]. The general model of versatile learning framework covers a wide reach, is not explicitly for the recommendation framework, and cannot completely address the issues. Subsequently, after top to bottom investigation of the important speculations and innovations of customized education and recommendation framework, this paper proposes a customized learning resource assortment framework model in light of the general model of recommendation framework and the general model of versatile learning framework is shown in Figure 1.

The model not only includes the basic modules and optional implementation innovations of the customized recommendation process for learning resources yet additionally incorporates the learning hypothesis that can be utilized as a help. It can give direction to the development of this point and even a customized recommendation procedure for learning resources for people in the future. Fluffy grouping is a strategy to order target objects by involving the similitude relationship in fluffy mathematics [6]. The center of the versatile recommendation model is reflected in the client fluffy bunching part; that is to say, the client customized model is laid out by working out the client's advantage in teaching resources, and the grouping technology is used to cluster the users with similar preferences. Predict users' preferences for unknown teaching resources according to the similarity of teaching resources in similar groups [7]. On this basis, complete the user-based collaborative filtering recommendation algorithm, rank their satisfaction according to groups, and generate the top-N teaching resource recommendation set [8]. The adaptive classification management model of teaching resources based on fuzzy clustering is as shown in Figure 2.

The purpose of adaptive recommendation is to provide personalized teaching resources for users with different retrieval intentions, and obtaining users' retrieval intentions is a crucial prerequisite for the ultimate realization of this purpose [9]. In the conventional network resource system, the resource retrieval intention expressed by users is generally expressed by scoring data that can reflect their interest characteristics. For example, the recommendation system of various film and music resource websites adopts the user active scoring system. Through the classification of learning results and the proposal of a nine-stage teaching procedure, it has an important impact on teaching design [10]. In learning activities, teaching activities can be organized in the order of students' learning activities. The specific teaching examples are designed as in Table 1.

In the teaching resource recommendation system, if explicit scoring is used to express the user interest of

resources, it will reduce the usability and accommodation of the framework. Simultaneously, the client interest offset of target resources cannot be gathered in time. Truth be told, clients' web-based conduct frequently suggests their advantage in target teaching resources [11]. For instance, assuming the client peruses the brief teaching resource page in under one moment, it implies that the client is not happy with the ongoing teaching resources or has low interest. Assuming there are downloading, printing, gathering, or saving activities, it demonstrates that the client is happy with or keen on the ongoing teaching resources. The fundamental standard of fluffy grouping for clients of teaching resources is to bunch clients through client portrayal records or at least the level of clients' advantage in the objective teaching resources [12]. The client's advantage can be depicted by vector space model. Toward the start of grouping, a delegate client is chosen as the bunching focus of this sort of clients, and the bunching focus is progressively changed by the likeness between the ongoing client and the grouping place until the preset limit is met, and at long last, the fluffy grouping of the objective teaching resource clients is created. The estimation recipe of similarity is as follows:

$$ SA'_{v,r} = \frac{\gamma \sum_{k=1}^{n} \left(\mu_k(w) \overline{-\lambda(w)} \right)}{\sum_{ueU} \left(A_{u,i} + \bar{A}_i \right) - \mu_k}. \tag{1} $$

Among them, $\mu_k(w)$ is the user μ_k interest preference value for the fuzzy cluster $A_{u,i}$ of teaching resources, and $\lambda(w)$ is the average interest preference value of users $\bar{A}_i$ for all fuzzy clusters of teaching resources. User $p_{nt,j}$ representation of teaching resources is consistent with that of user $ns_{i,nt}$. after the client's fluffy grouping not set in stone, SA_w clients in the bunch where the client to be suggested belongs and their nearest neighbors are selected according to the similarity, and the $\overline{SA_v}$ nearest neighbors' interest in the objective teaching resources is utilized to foresee the objective teaching resources r of the client to be suggested. The computation recipe is as per the following:

$$ S(w,r) = \overline{SA_w} + \sum_{t=1}^{k} ns_{i,nt} \cdot p_{nt,j} * \frac{SA'_{v,r} - \overline{SA_v}}{\sum_{v=1}^{n} 1} + \mu. \tag{2} $$

Interim AB addresses the closeness between client $w_{i,d}^2$ and its closest neighbor client $w_{i,S}^2$, κ represents the average interest of user σ, and E represents the interest of nearest neighbor user V in the target teaching resource R. According to this formula, the predicted values of all teaching resources RS in the teaching resource set R are calculated, and then, the top-N recommendation set is created by taking the principal n teaching resources from large to small according to the value of $S(w,r)$. The main function of the Chinese text personalized recommendation module is to use the personalized recommendation algorithm to compare the text vector model of learning resources with the learner interest vector model and recommend the first eight learning resources with high similarity to the learner interest vector model to
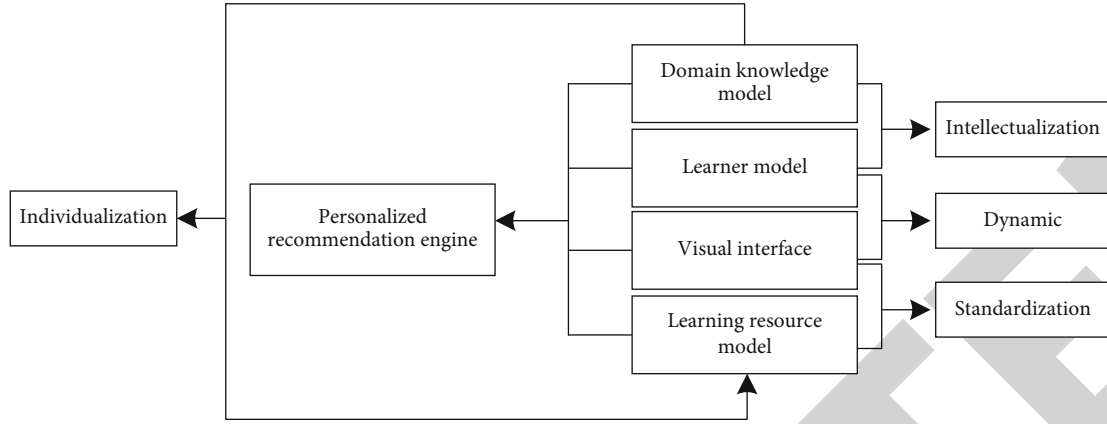
Figure 1: Model diagram of personalized acquisition system of learning resources.
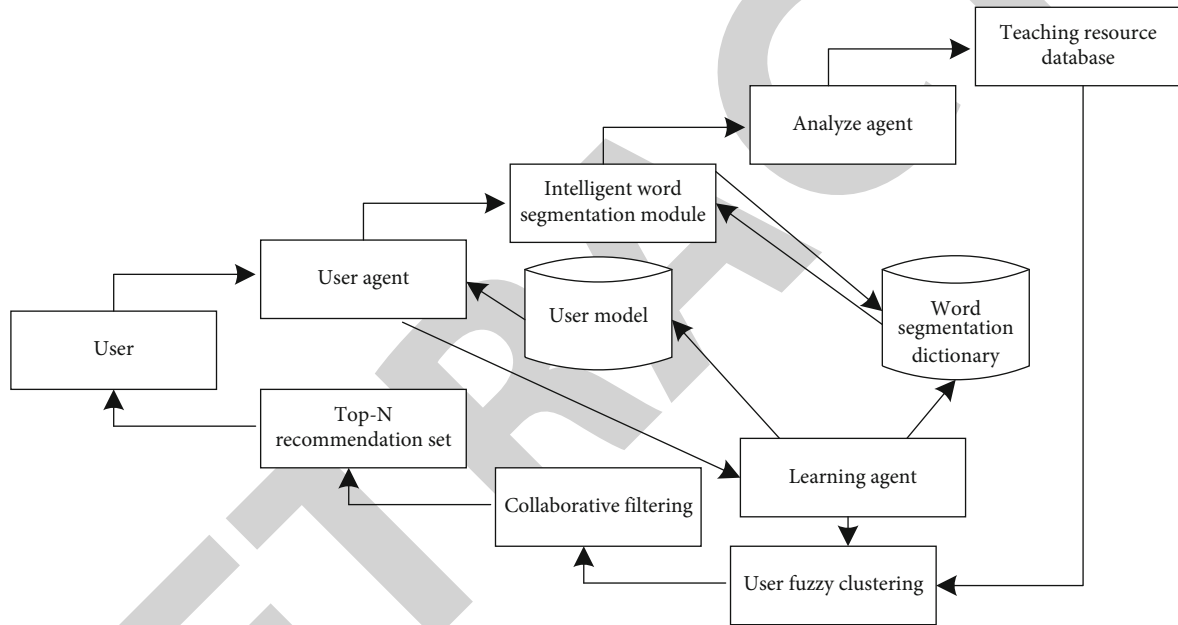

Figure 2: Adaptive classification management model of teaching resources based on school enterprise cooperation.

learners [13]. Because this paper chooses the vector space model to address the text resources and students' inclinations, it is considered to utilize the cosine comparability recipe to compute the likeness between the text vector model and students' advantage vector model. The customary cosine likeness computation equation is as per the following:

$$\text{Sim}(d, S) = \frac{\kappa - 1}{|S(w, r) - 1|} - R\sigma \frac{\prod AB + d}{E\sqrt{\sum w_{i,d}^2}\sqrt{\sum w_{i,S}^2}}. \qquad (3)$$

The formula only matches the feature words of the text vector model with the keywords of the learner's interest vector model to calculate the similarity between them and ignores the case that although the feature words in the text vector model do not appear in the learner's interest vector model, the words whose semantic correlation is greater than a certain threshold may exist in the learner's interest vector

model [14]. This learning resource should also meet learners' potential interests and should be recommended to learners. The customized recommendation procedure for learning resources in view of metaphysics is made out of student connection point and executive point of interaction. The student interface comprises of four modules: enlistment and login module, interest the board module, resource show module, and recommendation module [15]. The instructor manager interface comprises of three modules: learning resource the executive's module, cosmology the board module, and framework the board module. The specific module diagram is as shown in Figure 3.

Learning behavior is a sequence set of a series of abstract activities. In order to better evaluate members' interest in resources and determine the weight values of different behaviors, the above data need to be quantified [3]. The commonly used quantization method is the binary function method. When the learning behavior has only two states d and $t_{\max}(v)$, it can be quickly quantified through the binary

TABLE 1: Nine-stage ideological and political learning resource management procedure and learning activity design.

Internal construction process	Learning events	Learning stage	Learning activity design
Psychological perception	Attract learners' attention		Attract students' attention by presenting stimuli
Psychological expectation	Learning objectives of higher vocational learners	Learning preparation stage	What kind of learning goals can high-speed learners achieve and complete learning tasks through learning
Extract information	Stimulate learners' recall		Through certain pretest exercises, let learners recall what they have learned
Distinguish	Present stimulating material		Present different learning materials than before
Semantic coding	Provide learning guidance	Knowledge acquisition and practice	For learners to better construct the connection between old and new knowledge
React	Induce learner response		Give homework exercises
Give reinforcement	Provide feedback		Provide feedback
Extract knowledge	Assess learners' performance		Evaluate learners' homework
Extracting and storing knowledge	Promote knowledge retention and transfer	Migrate storage	Provide variant exercises for learners

function method. For example, the download behavior has only two states: occurrence and nonoccurrence; that is, if the behavior occurs, set its score value to 1; otherwise, the score value is t_i. However, this method also has some limitations. For example, different students may watch videos different times [16]. The binary function method ignores the different preferences of different members for the same resource in the scoring process, which reduces the accuracy of prediction scoring. To work on the proficiency of measurement and work on the precision of some learning behavior data prediction scores, this paper quantifies them in the following ways, as defined below:

$$\text{Interest}(T)_w = \frac{\sigma\left(\sum_{i=1}^{d} t_i - \text{Sim}(d, S)\right)}{d^* t_{\max}(v)}. \quad (4)$$

From the perspective of the participants of the course learning platform, there are four types of main participants in the platform [17]. Among them, if students do not log on to the platform, they are tourists. Tourists can only browse resources, not comment on resources, nor participate in the discussion of the learning community and obtain resource recommendations: if students log on to the platform, they can enter their own learning home page, browse videos, and learn courses [18–21]. Participate in community discussions, obtain recommended resources, etc. Teachers are the managers of all resources. They upload and update resources to meet the needs of more learners: background management is mainly responsible for maintaining the platform. Their main business functions are as shown in Table 2.

In addition to the basic functions of resources, news, announcement, and browsing, this paper adds a data collection module and an interactive module of the learning community. In the learning community module, students can communicate with other members and obtain the recom-

mended list of resources. However, these functions can only be used after students log in to the platform.

2.2. Adaptive Management Evaluation Algorithm of Ideological and Political Teaching Resources. At present, although the recommendation framework has been broadly utilized in many fields and numerous analysts and designers are contemplating and utilizing customized recommendation innovation, there is no unmistakable meaning of the recommendation framework. The primary undertaking of the recommendation framework is to associate clients and data resources to assist clients with finding data resources valuable to them. Simultaneously, it additionally permits data resources to be introduced to clients keen on them [3, 22–24]. The general model of the recommendation framework is displayed in the figure. It is made out of three modules: client model, recommendation object model, and recommendation calculation. The recommendation calculation module contrasts the client model and the article model. Sort and suggest the items that clients are probably going to be keen on the clients. From the above presentation, it very well may be seen that the meaning of the recommendation framework and the general model of the recommendation framework are basically situated to the business field, and there is not a lot of thought on the use of the recommendation framework in the field of education. Nonetheless, it actually has a specific reference for an incentive. From the meaning of a broadly utilized recommendation framework, it very well may be expanded that a recommendation framework in the field of education ought to be a framework that utilizes web-based learning sites to give students learning resource data and ideas to assist students with concluding what content to realize. The primary assignment is to associate students and learning resources to assist students with tracking down important learning resources for them and likewise permit learning resources to be introduced to students keen on them. The general model of recommendation
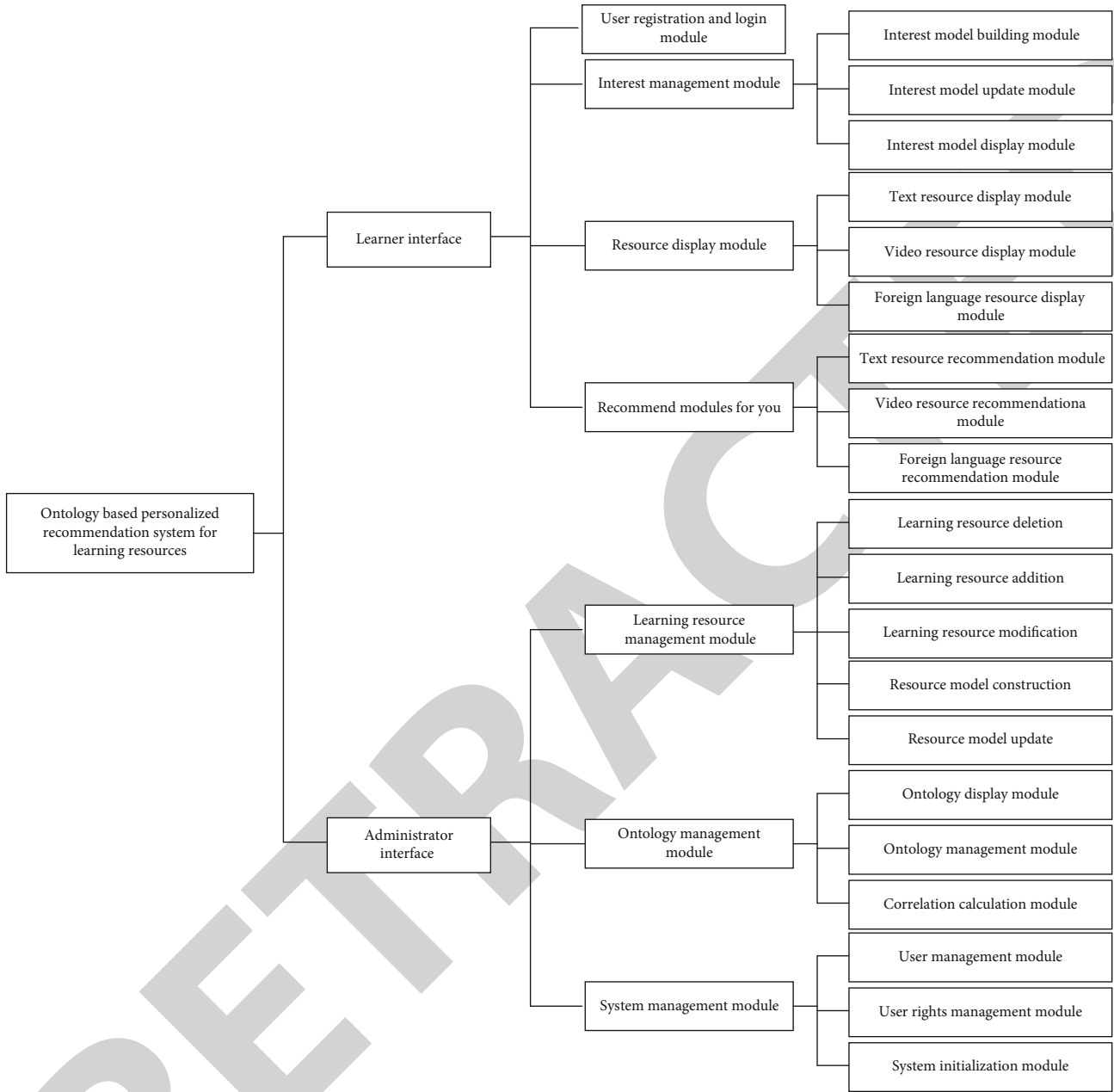
FIGURE 3: Ideological and political teaching resource management function.

TABLE 2: Main business functions of information recommendation platform.

Participant	Business function
System administrator	Manage students, manage resource recommendation module, etc.
Teacher administrator	Manage course resources, video resources, and download resources and manage the learning community
Study	Learn course resources, watch learning videos, and participate in community discussions
Tourist	Study the course, and check the message

framework can likewise give a reference to the development of a customized recommendation framework model of learning resources as shown in Figure 4.

In order to make better resource recommendation for nonmajors and avoid the defects of user-based and project-based collaborative filtering algorithm in practical application $R_{i,k}$, this paper proposes the following algorithm, which combines user-based $\overline{R_i}$ and project-based collaborative filtering algorithm $\overline{R_u}$ and adopts hybrid recommendation and Pearson similarity algorithm $R_{u,k}$, and the similarity
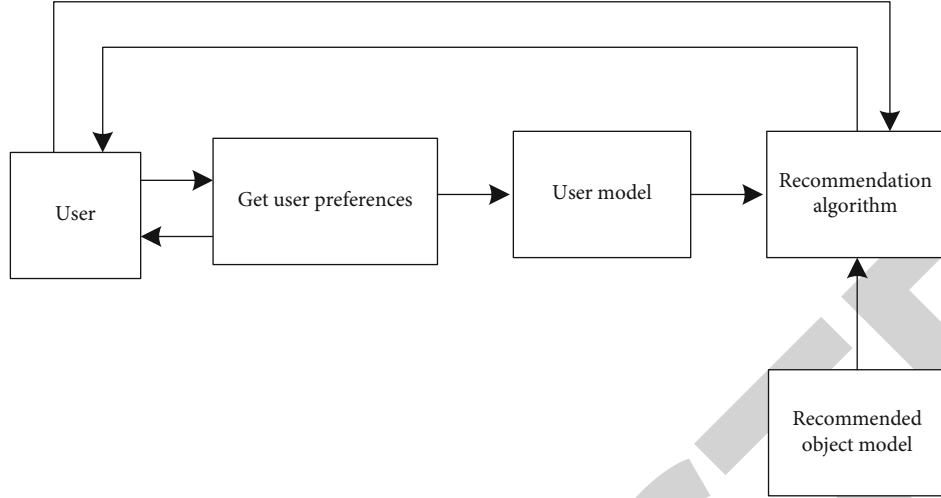
Figure 4: General model of the recommendation system.

sim (U, I) between target user u and user I is

$$\text{Sim}(u, i) = \frac{\sum_{k \in I_{uu}} \left(\text{Interest}(T)_w - 1\right)}{\sqrt{\sum_{k \in I_{ut}} \left(R_{i,k} - \overline{R_i}\right)^2} \sqrt{\sum_{k \in I_{uj}} \left(R_{u,k} - \overline{R_u}\right)^2}}. \quad (5)$$

Search the entire user set, and select the first q clients with the best similitude to client as the closest neighbor set n of client Y. The predicted score P of target user u on project J is

$$P_{u,j} = Yq + \frac{\sum_{n \in N_\alpha} \text{Sim}(u, i)(\lambda - \sigma)}{n \sum_{n \in N_u} \text{Sim}(u, i)}. \quad (6)$$

Combined with the research object of this paper, model fusion refers to using a certain preference fusion strategy to obtain the score of the group on the learning resources based on the score data of the learning members of the learning local area on the learning resources and then utilizing the customary collaborative filtering recommendation method to predict the score, so as to realize the group-oriented learning resource recommendation. Recommendation fusion is to obtain the prediction score of each member of the learning community on learning resources through recommendation technology, then fuse the prediction score of members based on a certain fusion strategy, obtain the prediction score of the group, establish the preference model of the group, and then produce the recommendation results. This study adopts the recommendation fusion strategy to obtain the group recommendation list by fusing the recommendation list of members, so as to realize the group-oriented resource recommendation. The intelligent recommendation fusion method of teaching resources is as shown in Figure 5.

Through the hierarchical relationship of the five subcategories of school enterprise cooperation, it can be concluded that more complex skill learning is based on simple skill learning. Therefore, for the identification and concept learning in the primary stage, the content organization of the learning platform should focus on well-structured domain knowledge, and the content presentation should focus on words and pictures and increase the interaction between the platform and learners. For the advanced stage of learning using rules, the learning platform should focus on non-well-structured domain knowledge, such as problem solving, and increase the diversity of learning evaluation methods in learning navigation, which is helpful for the inside and out advancement of understudies. In order to respect the learning characteristics of learners, according to the different learning stages of school enterprise cooperation, the learning platform provides learners with adaptive learning services and customize personalized adaptive learning navigation for learners which is shown Table 3.

Through the above analysis of learners' learning styles, according to learners' preferences for information input, organization, and processing stages, it can be concluded that the perception input dimension has an important impact on the presentation of personalized content on the learning platform, the organization dimension has an important impact on the provision of learners' practice, and the processing and understanding dimension has an important impact on the learning navigation provided by the learning platform.

2.3. Implementation of Adaptive Recommendation of Ideological and Political Teaching Resources. In rule-based recommendation, the system administrator formulates rules according to the static characteristics and dynamic attributes of users. Rules can be customized by users or discovered by data mining technology based on association rules. In the system of using rules for recommendation, the quality of recommendation depends on the quality and quantity of rules. A rule is essentially an if-then statement, which determines how to provide different services in different situations. The rule-based recommendation system generally includes three parts: keyword layer, description layer, and user interface layer as shown in Figure 6.

The bottom layer in the figure provides the required keywords for the upper layer description and defines the
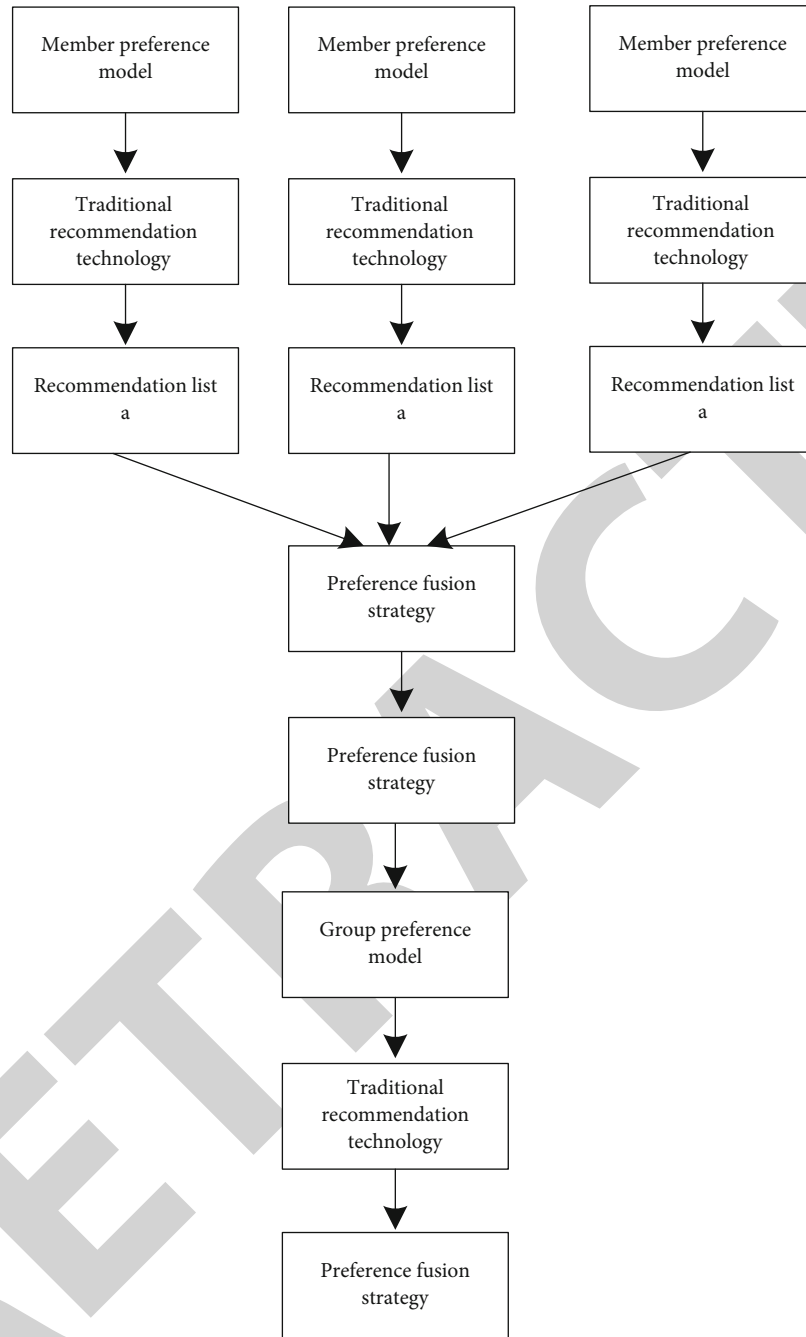
Figure 5: Intelligent recommendation fusion method of teaching resources.

dependencies between keywords. In this layer, you can also define the personalization rules of static attributes. The description layer above the keyword layer defines user and resource descriptions. This layer is specific to users and resources, so its personalization rules are dynamic. The user interface layer at the top layer recommends the resources meeting the rules to users according to the personalized rules defined in the following two layers. By comprehensively considering the learner's characteristic information and matching the resource information described in the resource database (resource form, difficulty coefficient, content correlation, etc.), recommend the learning resources most suitable for learners' learning, and in the personalized page design database, recommend the most suitable learning interface navigation. The recommendation mode of learning resources in ideological and political teaching is as shown in Figure 7.

Database often assumes a vital part in the stage. The underlying model of data set will influence the productivity of use stage and the acknowledgment of learning impact. Client model is utilized to portray, store, and deal with clients' inclinations and requirements. Since customized recommendation depends on the PC stage, in light of the fact that the client model is certainly not an overall portrayal of

Table 3: Personalized service based on learning objectives.

| Intelligence skill subclass	Personalized knowledge presentation	Personalized learning navigation
Distinguish	Mainly text and structure comparison diagram	Strengthen the interaction between the platform and learners, and make timely evaluation
Concrete concept	Add specific examples, mainly in picture and video formats	The platform provides timely feedback to learners
Define concepts	Pay attention to the relationship between old and new knowledge, and use the knowledge structure diagram	Add variant exercises
Rules and advanced rules	It is mainly based on learners' independent thinking, and the answers to exercises are not unique	Exercises are more difficult, and evaluation methods are diverse
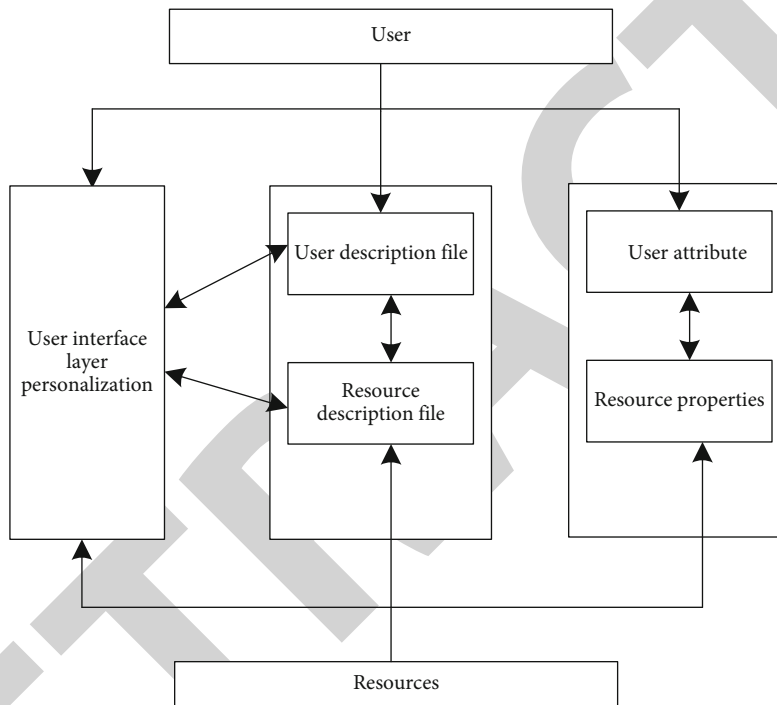
Figure 6: Characteristic information recommendation method of ideological and political teaching resources.

client interests, however, a calculation is situated, a formal depiction with explicit information structure. As the primary stage, client demonstrating is essentially to acquire information connected with keeping up with client interests, client needs, or propensities. The consequence of client displaying is to deliver a client model that represents the user's unique background knowledge or interests and needs. In order to respect the learning characteristics of learners, according to the different learning stages of school enterprise cooperation, learning level provides learners with adaptive learning services and customized personalized adaptive learning navigation for learners as shown in Table 4.

According to the behavior characteristics of e-learning actors, some controllable behaviors can be selected to count the behavior attributes. Through the statistics of behavior attributes and data, we can not only better grasp the information characteristics of learners but also help to select learning resources more suitable for learners' needs. The specific network behavior attributes are as shown in

Table 5. Finally, the behavior attributes and data are stored in the learner behavior feature database to prepare for the recommendation of later learning resources.

In the second stage of project matching, based on the established user model, various recommendation technologies will be used to find matching projects. In the recommendation output stage, these matching projects will be presented to users in the form of predicted value, top-N recommendation or other forms. Group teaching resources as per disciplines. For the objective clients, the resources they focus on are separated into two classifications: proficient resources and nonproficient resources. This division is straightforward and clear and makes the recommendation more designated and more proficient. These two sorts of resources can be isolated into the most recent resources, store resources, and resources important to clients. Explicit grouping structure graph. The ordered administration of ideological and political teaching resources is as shown in Figure 8.
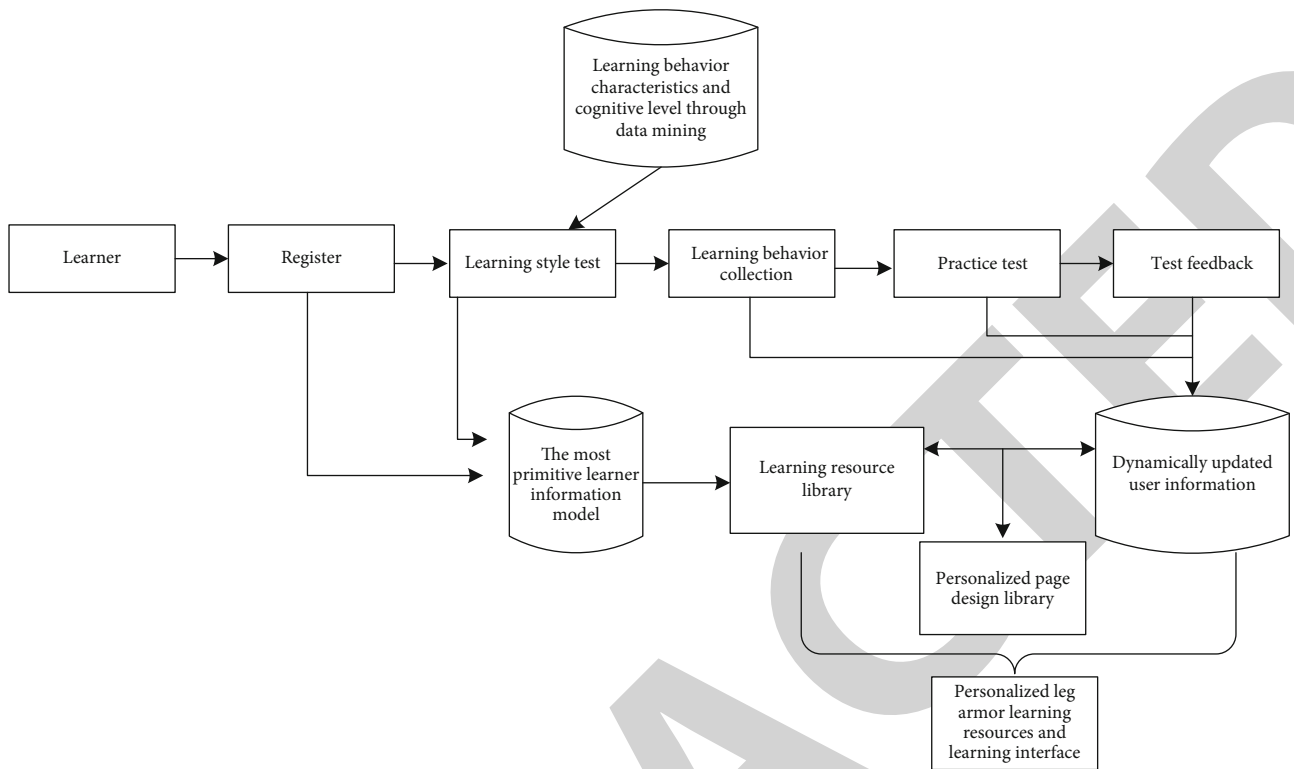
FIGURE 7: Recommendation model of learning resources for ideological and political teaching.

TABLE 4: Personalized services based on learning objectives.

Intelligence skill subclass	Personalized knowledge presentation	Personalized learning navigation
Distinguish	It is mainly text and comparison diagram	Strengthen the interaction between the platform and learners, and make timely evaluation
Concrete concept	Add specific examples	Give timely feedback to learners
Define concepts	Pay attention to the connection between old and new knowledge	Increase practice
Rules and advanced rules	Focus on learners' independent thinking	The difficulty of exercises is increased, and the evaluation is diversified

TABLE 5: Recommended behavior attributes of main teaching information.

| Major network behaviors	Specific behavior attributes
Browse the web	Website address, keyword, time
Browse learning resources	Subject, time, and login times of learning resources
Information search	Keywords, page stay
Resource download	Keyword, resource format
Favorite web page	Website address, website name
Send and receive email	Address, subject
Forum discussion	Number of posts read
Ask questions	Question topic, frequency
Question answering	Frequency and accuracy
Study notes	Subject, content, viewed learning materials
Personal learning archives	View time, grades, and comments
Job release	Content, format, and release times
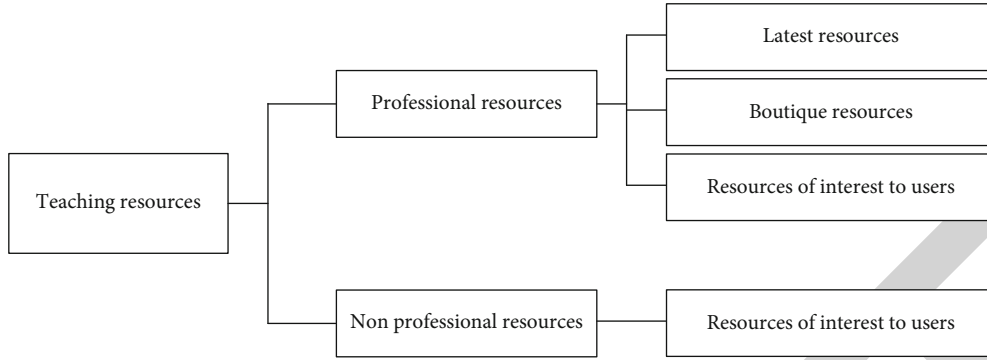
Figure 8: Classified management of ideological and political teaching resources.
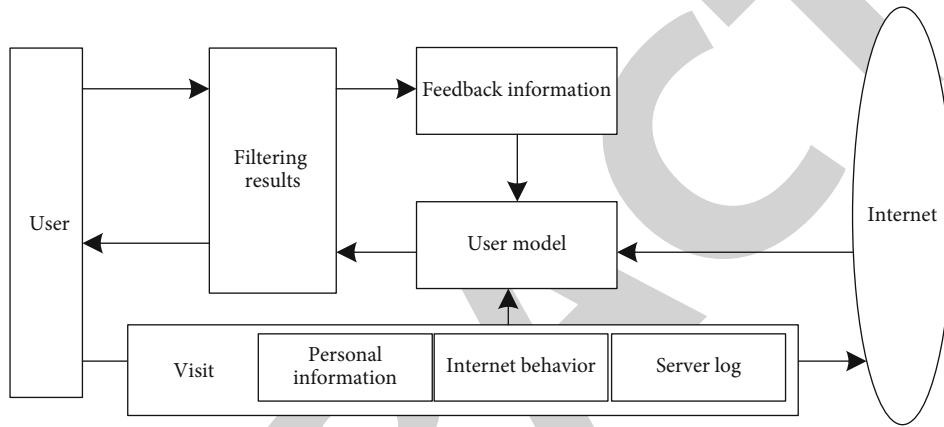

Figure 9: Modeling process of personalized recommendation system.

Table 6: Collection of ideological and political online teaching information training sets in different universities.

	Total posts (PCs.)	Statistical time (days)	Average daily posts (PCs.)	Posting user (person)	Average number of users (PCs.)
A university	16958625	865	19586.32	136525	133.25
B university	598562	798	758.65	768520	7.82
C university	3659856	865	4653.52	26525	141.32
D university	76558	912	85.21	7832	9.98

It tends to be seen that client displaying is the premise and center of customized recommendation and client model is the principal information wellspring of customized recommendation framework. Whether the client model can catch the genuine inclinations of the client's furthest degree decides the progress of recommendation, and its quality is straightforwardly connected with the nature of customized administration. Thusly, just a precise understanding of clients' inclinations and requirements can furnish clients with good recommendations. The demonstrating system of customized recommendation framework incorporates four errands: information assortment, model portrayal, model learning, and model update. The relationship is as shown in Figure 9.

There are numerous sorts of teaching resources; however, the essential disciplines they have a place with are extremely clear. We can be aware from the "proficient code" quality in the teaching resource model to understand the sensible administration and characterization of various kinds of teaching resources. In light of the above research content, the versatile management and recommendation of teaching resources can better ensure the recommendation effect.

3. Analysis of Experimental Results

The disconnected information is utilized for tests. The information is isolated into a preparing set and test set. The learning inclination model is laid out on the preparation set by the suggested strategy, and then, at that point, assessed in light of the expectation consequences of the test set. This paper utilizes the recommendation methodology in view of element disintegration machine to get the forecast score of learning local area individuals. To check the viability of its strategy, this paper looks at the conventional recommendation technique in view of client cooperative separating from the assessment file of recommendation exactness, which alludes to the occurrence between the anticipated score
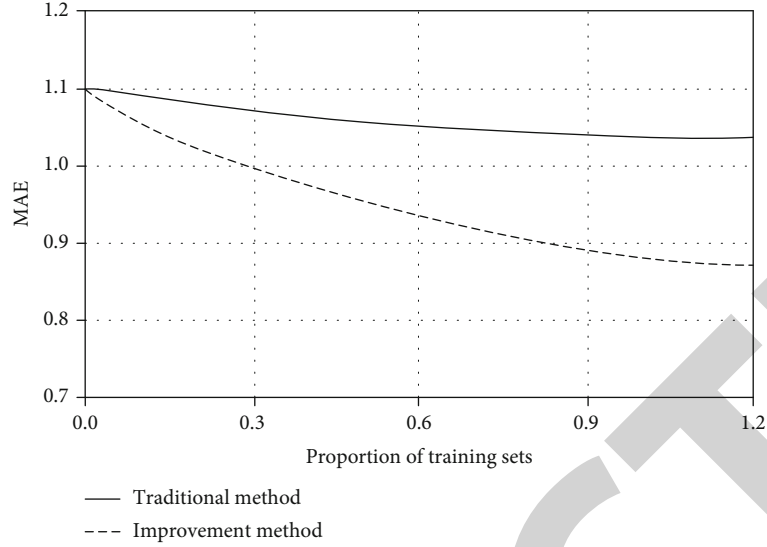
Figure 10: Influence of different proportions of teaching resource training set on recommendation.
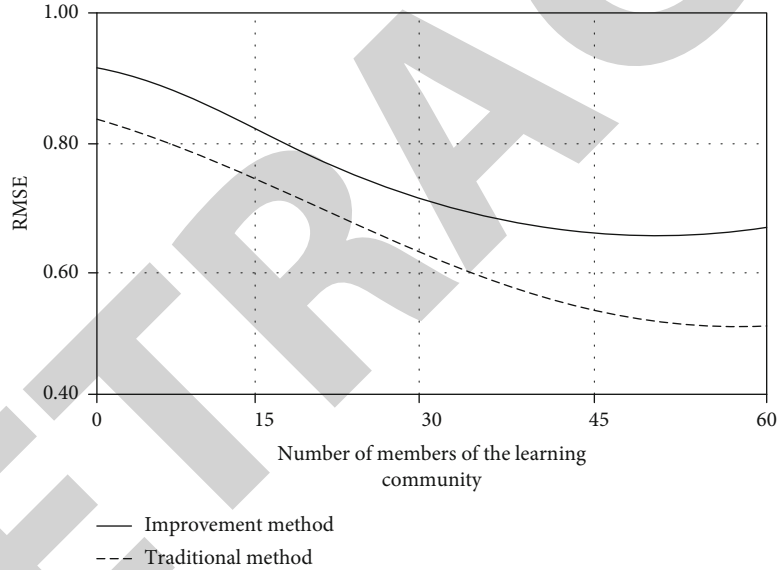

Figure 11: Comparison of RMSE values recommended by average fusion of teaching resources.

and the genuine score on the test set. The anticipated score is determined by displaying the preparation informational collection. Precision is by and large determined through root mean square blunder and mean mistake MAE. The estimation strategy for MAE is basic and straightforward: RMSE will increase the penalty of large error value in prediction score, and the requirements for evaluation are more strict. It is defined that in the test set, the actual score of learning community member u on resource n is R_{ui}, r_{ui} is the predicted score of member u on resource I trained according to the recommended method, T is the test set, and the calculation of root mean square error (RMSE) is as follows:

$$\text{RMSE} = \frac{\sqrt{\sum_{U,i \in T}(R_{ui} - r_{ui})^2}}{|T|}. \tag{7}$$

The mean error MAE measures the exactness of recommendation by ascertaining the distinction between the score of the test set and the anticipated score. The mean mistake MAE is characterized as

$$\text{MAE} = \frac{\sum_{U,i \in T}|R_{ui} - r_{ui}|}{|T - n|}. \tag{8}$$

To confirm the viability of learning local area situated recommendation, this paper plans to analyze the gathering recommendation technique in view of mean combination system. Nonetheless, the learning local area arranged recommendation technique could not utilize the root at any point mean square mistake (RMSE) and normal blunder MAE to work out the exactness, on the grounds that contrasted and the individual situated recommendation precision
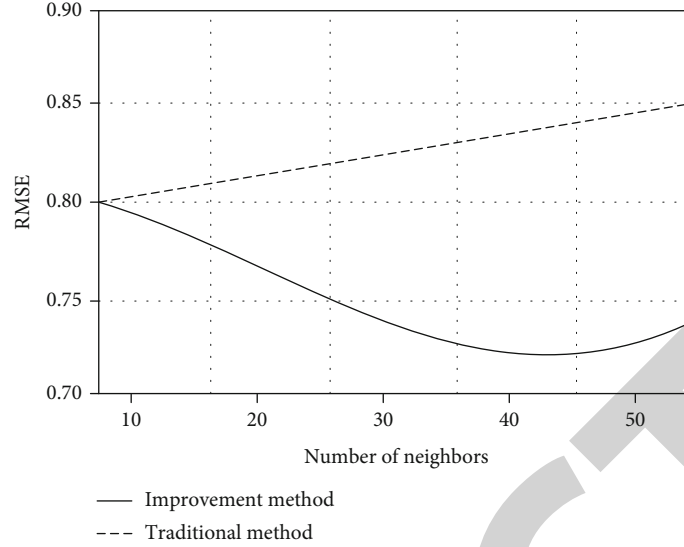
FIGURE 12: Comparison test results of information recommendation accuracy.

assessment strategy; the genuine score of the gathering on resources does not exist unbiasedly; however, it should be gotten by combination through examination. In this manner, the above assessment pointers are not reasonable for the assessment of the precision of gathering recommendation. To check the precision of gathering recommendation, this paper ascertains the exactness of gathering recommendation as indicated by the assessment record of gathering recommendation. The particular computation technique is as per the following:

$$\mathrm{RMSE}_g = \sqrt{\frac{\sum_{i=0}^{n} \left(R_{ui} - r_{gi} \right)^2}{n}}. \tag{9}$$

The RMSE determined by the recommendation technique proposed in this paper is contrasted and the gathering recommendation strategy in view of mean procedure to confirm the exactness of recommendation. To concentrate on the general action of the college understudy discussion, the chosen agent college data is ordered, arranged, and considered which is shown in Table 6. A histogram is attracted by the all-out number of posts, the typical number of posts each day, and the typical number of posts per client.

When the proportion of training sets is different, the recommendation results of the recommendation algorithm are different. In this group of experiments, eight different training set ratios are selected, the user's score on a certain item is hidden, and the number of nearest neighbors is 30. The experimental results are as shown in Figure 10.

In order to verify the recommendation effect for learning community, the scale of learning community $s = \{2, 5, 18, 31, 50, 62\}$ selected in this paper is compared with the accuracy of group recommendation based on mean fusion strategy. The specific experimental results are as shown in Figure 10.

The comparative recommendation method in the experiment is the recommendation based on the mean fusion strategy, which means that when the recommendation list

of members is fused to obtain the group recommendation list, the weight values of all members are defined as 1 without considering the different weights of different members in the learning community. It tends to be seen from Figure 11 that the RMSE's worth of the recommendation calculation proposed in this paper is undeniably not exactly the RMSE_g of the recommendation calculation in view of the mean combination procedure. The more modest the RMSE esteem, the more modest the mistake, and that implies that the aftereffect of resource recommendation for the learning local area in this paper is more precise. During the investigation, the quantity of closest neighbors of the objective clients of teaching resources expanded from 20 to 50, and the step size was 5. The precision of the customary cooperative separating recommendation strategy and the technique in view of this paper were calculated and compared, respectively. The experimental results are as shown in Figure 12.

The exploratory outcomes show that the proposed strategy has more modest MAE esteem than the conventional cooperative separating recommendation technique, which shows that the precision and nature of teaching resource recommendation expectation are better. This is on the grounds that the conventional cooperative separating recommendation calculation looks the closest neighbor of the objective client in all client spaces, while the recommendation calculation in view of fluffy grouping looks through in the bunched client space, so the exactness of recommendation is enormously gotten to the next level. Besides, with the increment of the quantity of closest neighbors of target clients, the more prominent the distinction between their MAE, showing that the recommendation forecast precision and quality advantages based on this method are more obvious.

4. Conclusion

With the acceleration of educational informatization, intelligent adaptive recommendation has become an important

part of the construction and application of teaching resources. Aiming at the problem that the accuracy and personalization of the feedback results of conventional resource retrieval and traditional recommendation methods are low due to the increment of the quantity of teaching resources, a cooperative separating recommendation strategy in view of fluffy grouping is proposed. The trial results show that the recommendation quality and exactness have been extraordinarily gotten to the next level. Moreover, this paper likewise presents canny word division innovation and portable specialist innovation to upgrade the mental prowess of various clients in the recommendation cycle and work on the fulfillment of resource clients. Notwithstanding, explorations likewise show that with the increment of the quantity of closest neighbors of the objective client, the time effectiveness of resource recommendation will be decreased somewhat, albeit this interaction can be determined disconnected. Thusly, the future work will make further exploration on working on the nature of resource recommendation and successfully working on the constant execution of the calculation.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

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