

Retraction

Retracted: A Personalized Recommendation System for English Teaching Resources Based on Multi- K Nearest Neighbor Regression Algorithm

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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. Tang and Y. Yu, "A Personalized Recommendation System for English Teaching Resources Based on Multi- K Nearest Neighbor Regression Algorithm," *Security and Communication Networks*, vol. 2022, Article ID 7077123, 11 pages, 2022.

Research Article

A Personalized Recommendation System for English Teaching Resources Based on Multi-K Nearest Neighbor Regression Algorithm

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In order to ensure the quality of resource recommendation and solve the problems of low recommendation accuracy, long recommendation time, and high data loss rate in the process of resource recommendation in traditional methods, a personalized recommendation system of English teaching resources based on the multi-K nearest neighbor regression algorithm is designed. According to the overall architecture of the personalized recommendation system of teaching resources, this study designs the resource browsing function module, teaching resource detailed page recommendation module, and teaching resource database. Based on the basic idea of the multi-K nearest neighbor regression algorithm, in order to avoid the loss of important data in English teaching resource recommendation and reduce the data loss rate, a missing data reconstruction algorithm of English teaching resources is proposed. Finally, the path interest of student users is considered from the selection of browsing path and access time to realize the personalized recommendation of English teaching resources. The experimental results show that the system has high resource recommendation accuracy, short recommendation time, and low data loss rate.

1. Introduction

Network teaching has become a new learning mode, but there are still many defects in the current network learning resource system: there are so many learning resources that learners cannot find the required resources quickly like looking for a needle in a haystack; learners need to manually input descriptive words for search, and the system cannot actively recommend according to the user's own information [1]. These defects make network teaching lose its original advantages. Therefore, it is urgent to integrate personalized services into network teaching [2]. In this way, through the active push of the system, users can quickly and accurately obtain the required resources without having to search and find resources themselves, which improves the efficiency of users looking for resources and saves users a lot of time [3]. In addition, personalized recommendation

technology can ensure the quality of resource recommendation and improve resource utilization. In this context, some scholars have put forward some practical methods[4].

Reference [5] proposes an online learning resource recommendation method based on ontology and cyclic neural network. Aiming at the online learning environment and its generated data, the ontology method is used to model and represent the domain knowledge of learners and learning resources, and the cyclic neural network is used to mine learners' learning patterns to obtain the final resource recommendation list. The experimental results show that this method can effectively recommend a large number of teaching resources and has certain comprehensiveness. However, in the design of recommendation method, the problem of personalization is ignored and the accuracy of resource recommendation is not high. Reference [6] proposes an online learning resource recommendation model

based on the multi-objective optimization strategy. Within the learner planning time, taking the maximum preference of learners for learning resource types and the best fitness of difficulty level as the optimization goal, a multi-objective particle swarm optimization algorithm with the ability to learn from the neighbor mean and explore new areas is designed, which is a complete online learning resource recommendation. This method can improve the recommendation accuracy and performance of online learning resources, but it will consume more time and the recommendation efficiency is not high. Reference [7] proposes a personalized learning resource recommendation method based on three-dimensional feature collaborative domination. Firstly, by improving the matching relationship between learners and online learning resource features, a personalized learning resource recommendation model based on three-dimensional feature collaborative domination is established and described parametrically. Secondly, a binary particle swarm optimization algorithm based on the Gaussian membership function fuzzy control is designed to solve the objective function of the recommendation model. Finally, under multiple evaluation indexes, five groups of comparative experiments verify that the recommendation method has good recommendation performance, but the data loss rate is high in the recommendation process.

The advantages of content-based recommendation lie in the user independence, the interpretability of recommendation results brought by high project transparency, and the ability of new projects to enter the recommendation list. However, it also has some problems, such as the acquisition of domain knowledge, limited analyzable content, and obsolete recommended content. The collaborative filtering method uses the user's history to make recommendations. The so-called collaboration is to work together. Mutual help means that the target user has common preferences with similar users and shares opinions with others. It has become one of the most important and widely used technologies in the recommendation system because it does not need to master special domain knowledge, item attributes, and context features.

In the process of the continuous and rapid development of Internet and information technology, the number of users is increasing, the types of items are becoming more and more abundant, and the interaction modes are more diversified. Accordingly, the research and development of recommendation methods are also facing many challenges, and the details are as follows:

- (1) Data sparsity: with the development of Internet, especially mobile Internet, the number of users and items increases sharply. Accordingly, the two-dimensional list of users and items increases sharply, which leads to the increasingly sparse data sets available in the recommendation system.
- (2) Failure problem of classical similarity measure: in the scoring matrix with prominent sparsity problem, there are a large number of phenomena that "there is only one or two common scoring items between two users."

- (3) The sensitivity of nearest neighbor recommendation to sparse data: in the case of sparse data, the problem of limited common scoring items will also lead to the fact that the nearest neighbor-based recommendation method can only obtain a very limited number of nearest neighbors, which will significantly affect the prediction accuracy and robustness of the recommendation system.

To solve the problems of low recommendation accuracy, long recommendation time, and high data loss rate in the resource recommendation process of the above traditional methods, a personalized recommendation system of English teaching resources based on the multi- K nearest neighbor regression algorithm is designed. The main innovations of the system are as follows:

- (1) The overall architecture of the personalized recommendation system of teaching resources is designed. The component modules of this architecture are as follows: consulting module, transmission module, scoring and comment function module, resource management function module, message reminder function module, and teaching resource detailed page recommendation module.
- (2) This study designs a teaching resource database with five functions: resource collection, resource sorting and classification, resource utilization, statistical analysis, and system management.
- (3) Based on the basic idea of the multi- K nearest neighbor regression algorithm, a missing data reconstruction algorithm of English teaching resources is proposed, which is used to reduce the data loss rate.
- (4) Based on the choice of browsing path and access time, this study analyzes the interest of students' access path and realizes the personalized recommendation of English teaching resources.

The organization of the study is as follows: in Section 1, we introduced the network teaching and the recommendation system. Section 2 provides the framework of the network teaching personalized recommendation system. The proposed method is presented in Section 3, and in Section 4, we illustrated the experimental information and the results of the experiments; finally, Section 5 provides the conclusion.

2. Design of a Personalized Recommendation System for Teaching Resources

2.1. Analysis of the Overall Architecture and Functional Modules of the Personalized Recommendation System for Teaching Resources. The personalized recommendation design of teaching resources is mainly aimed at student users. When the student user browses the personalized recommendation homepage and page, the recommendation system will make different recommendations. When users browse the home page, the recommendation system will

recommend according to users' browsing habits and the attributes of teaching resources. When the user browses the detailed page of a teaching resource, the recommendation engine will recommend similar to the current resource and that the user may like according to the current teaching resource attributes and user habits. The personalized recommendation system can be divided into different functional modules. Figure 1 shows the overall architecture.

According to the overall structure of the personalized recommendation system of teaching resources, combined with the needs of students and users, the functional modules of the system are analyzed in detail.

2.1.1. Lookup Module. Users can view all resources and view them in the form of ranking, such as release time and download times. They can also search the resources under the categories they want to view according to categories and search the resources they need through keywords. The detailed information of the resource can be displayed to the user intuitively, such as resource classification, download times, resource comment, and other resource information. Figure 2 is a block diagram of the resource browsing function modules.

2.1.2. Transmission Module. After the login is completed, files can be transferred, including upload and download functions, and the content uploaded by ordinary users will not be directly disclosed. Teachers and users are required to log in, and then, the documents can be examined and approved, and only when they are qualified, they can be made public. If they pass the approval, they can be published.

2.1.3. Resource Management Function Module. Editing includes modifying resource title, resource classification, deleting invalid or unnecessary resources, and making the resource base more standardized and reasonable. Teacher users can also dynamically manage resource classifications. The operation of deleting a classification can delete an empty classification, and there are no resources under the classification, or under a certain resource classification, when a certain type of resource expires or is no longer needed, the purpose of deleting resources in batches according to the resource classification can be achieved. The related content is deleted to purify the website and better help student users locate resources quickly and accurately and find required.

2.1.4. Message Reminder Function Module. When the uploaded file is not approved, a message is sent to the user; when users get new comments on the uploaded resources, they will also notify users through the station message, and users can receive the evaluation of related documents and urge them to upload higher-quality documents later, to achieve the purpose of optimizing the teaching resources in the personalized recommendation system.

2.1.5. Recommended Modules on the Detailed Pages of Teaching Resources. When accessing that detailed content page, the recommendation system will recommend resources similar to the currently browsed teaching resources to the current student user according to the teaching resources currently browsed by the student user and the past teaching resource preferences of the current student user.

2.2. Teaching Resource Database Design. Teaching resource database is a network application system based on campus network, which needs three servers: one application server is used to deploy teaching resource management software; one multimedia file server for storing uploaded video files and other teaching resource files; and one database server is used to deploy the data required by the personalized recommendation system of teaching resources. Hardware firewall equipment is set before the application server to intercept attacks and ensure the security of the server area. The data collection/audit area has high read and write permissions to the database, while the data utilization area has low-access permissions and only read permissions to the database. Figure 3 shows the network topology of teaching resource database.

The teaching resource database management software adopts the browse/client (B/S) structure, the development tool selects the most popular Python development platform, and we also use the TensorFlow framework as our computation framework. Meanwhile, Microsoft SQL Server 2019 is used as the database, and the FTP protocol is used for file transfer between the application server and the multimedia file server.

Teaching resource database management software includes five functions: resource collection, resource sorting, resource utilization, statistical analysis, and system management, as shown in Figure 4.

Full attention must be paid to the security backup of the teaching resource database to avoid a devastating blow to the database due to natural disasters, hardware failures, and hacker attacks. The backup of the teaching resource database should adopt multiple sets of the multisite perfect strategies. The content of the backup should not only include the teaching resource data itself but also the management software that supports the database. The backup of the management software is relatively simple, and the program can be backed up with mobile hard disc, CD-ROM, and other media and stored in different locations. The backup of teaching resource data is relatively complicated, and a combination of online backup and offline backup can be used: online backup can set tasks on the database server, automatically back up the database regularly, and can also use tape drive equipment for backup; offline backup can use mobile hard discs, optical discs, and other media for backup and save multiple copies in different locations. The disc used for backup should be file-grade discs produced by JVC or Tsinghua Tongfang to ensure long-term storage of data.

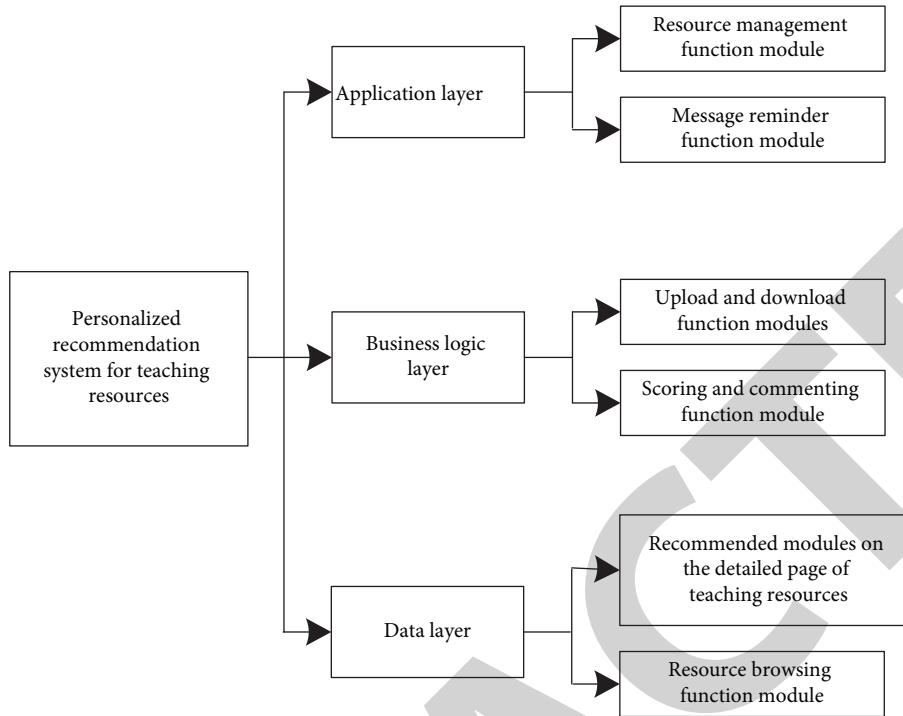


FIGURE 1: Schematic diagram of the overall architecture of the personalized recommendation system for teaching resources.

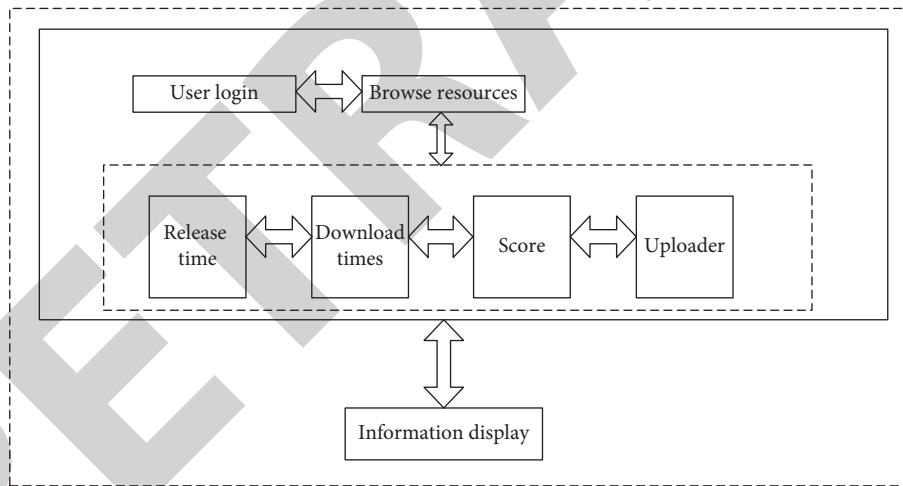


FIGURE 2: Block diagram of resource browsing function modules.

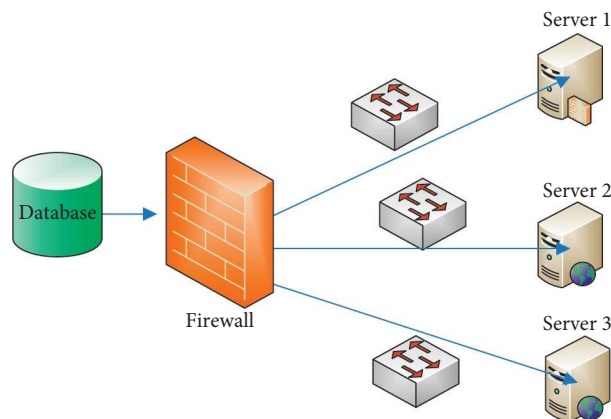


FIGURE 3: Network topology structure of teaching resource database.

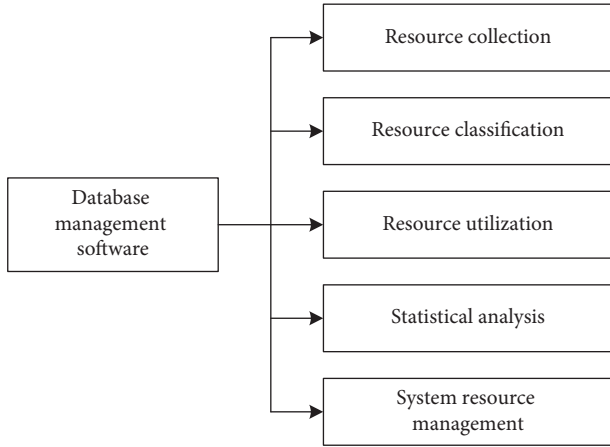


FIGURE 4: Functional structure of teaching resource database software.

3. Personalized Recommendation Algorithm for English Teaching Resources

According to the overall architecture of the teaching resource personalized recommendation system designed above, with the support of the recommendation system function module and the database software function module, the personalized recommendation algorithm for English teaching resources is designed to further enhance the resource recommendation effect.

3.1. Reconstruction of Missing Data of English Teaching Resources Based on Multi-K Nearest Neighbor Regression Algorithm

3.1.1. Multi-K Nearest Neighbor Regression Algorithm. The basic idea of the multi- K nearest neighbor regression algorithm is to give a training data set, find the K instance closest to the instance in the training data set for a new input instance, and calculate the weighted average value of the label attribute of the instance [8]. The Euclidean distance function is generally used to describe the distance as the label attribute value of the input instance:

$$\text{distance}(s_i, s_j) = \sqrt{(s_{i1}, s_{j1})^2 + (s_{i2}, s_{j2})^2 + \dots + (s_{in}, s_{jn})^2}. \quad (1)$$

Here, s_{ij} represents the j th attribute value of the i th instance and n represents the number of attributes.

How to find the k data closest to the instance to be recommended from the data set has a very important impact on the personalized recommendation of English teaching resources. The following is a specific analysis of the k value.

If the value of k is small, it is equivalent to speculating on the training examples in the small neighborhood. Only the training examples close to or similar to the input examples will work on the recommendation results. At this time, the problem is that the estimation error of “learning” will increase; that is, the reduction in k value will make the

recommendation system complex and prone to overfitting; if the value of k is large, it is equivalent to recommending training instances in a large neighborhood. At this time, training instances that are far away (not similar) from the input instance will also work on the recommendation results, making the resource recommendation results deviate, and the increase in the value of k means that the recommendation system becomes simple; in extreme cases, the value is the number of all training instances. At this time, no matter what the input instance is, the recommendation result will be exactly the same. Such a recommendation system is too simple and ignores a large amount of useful information in the training instance. Therefore, it is necessary to select the optimal k value [9].

3.1.2. Reconstruction of Missing Data in English Teaching Resources. Based on the basic idea of the multi- K nearest neighbor regression algorithm, to avoid missing important data in English teaching resource recommendation and reduce the data loss rate, a missing data reconstruction algorithm of English teaching resources is proposed, which solves the problem of missing data of English teaching resources through the multi- K nearest neighbor regression algorithm. In addition to the above correlation, some data in the English teaching resource database also have significant correlation and periodicity between parameters. Therefore, this method focuses on the second-order correlation between parameters and takes the recovery matrix as close as possible to the original matrix as the optimization goal of the algorithm, that is,

$$\min \|A - B\|_G^2. \quad (2)$$

Here, A represents the recovery matrix; B represents the observation matrix; and $\|\cdot\|_G^2$ represents the second-order Frobenius norm.

The multi- K nearest neighbor regression algorithm is used to perform regression analysis and reconstruction on the transformation matrix to improve the accuracy of data reconstruction. The multi- K nearest neighbor regression algorithm is a simple and easy to implement algorithm that uses similarity measures such as distance functions to achieve numerical target prediction [10]. For data association reconstruction in the time dimension, traditional methods mainly have problems such as the difficulty of automatically determining the k value, the sensitivity of sample noise, and the change in neighbor structure during low-dimensional projection. For this reason, this study introduces least squares in the multi- K nearest neighbor regression algorithm. Multiplication is taken as the loss function, and the least-squares model can be expressed as follows:

$$\min_D \|B - D^T A\|_G^2. \quad (3)$$

For the loss function of the least-squares method, when A is not the full rank of the column, or the linear correlation between some columns is large, the determinant of $D^T A$ is close to 0, that is, A is a nonsingular matrix, the error in

calculating $(D^T A)^{-1}$ will be large, and it is difficult to ensure that there is a unique optimal solution. The penalty term constraint is introduced on the basis of the least-squares method. Although the unbiased property is lost, high numerical stability and calculation accuracy can be obtained. In particular, adding a constant to the main diagonal elements can make the matrix full rank and meet the conditions for solving the optimal solution. When there are few training data, ridge regression with regularization penalty term has better effect, so it has the following:

$$\min_D \|B - D^T A\|_G^2 + \partial \|D\|_2^2. \quad (4)$$

The more items in formula (4) than formula (5) are regularization factors, where ∂ is a coefficient greater than zero, which controls the strength of the penalty term. Using l_1 norm as penalty term can ensure the uniqueness of the optimal solution, but the obtained solution may not be sparse, which will affect the value in the multi- K nearest neighbor regression algorithm and affect the stability and reliability of the result. Therefore, $l_{2,1}$ norm is used to replace the following:

$$l_{2,1} = \eta \sum_{i=1}^n \sum_{j=1}^n s_{ij}^2. \quad (5)$$

$l_{2,1}$ norm combines the sparsity of l_1 norm well and has the characteristics of l_2 norm to prevent overfitting of loss function. It is more suitable for data processing of English teaching resources with high noise. The l_2 norm in formula (5) is replaced with formula (4), and then, we get the following:

$$\min_D \|B - D^T A\|_G^2 + \partial \|D\|_{2,1}^2. \quad (6)$$

Since formula (6) is a convex function, we can take the derivative of d_i ($1 \leq i \leq N$) and make it 0, and we can get the following:

$$d_i = \frac{\eta \|D\|_{2,1}}{\eta K_i}. \quad (7)$$

Here, K_i represents a diagonal matrix, where the h th diagonal element is $1/2 \|d^h\|_2$.

Combining formula (7) with formula (6), we can obtain the following:

$$d_i = (AA^T + \partial D)^2 + \|D\|_{2,1}^2. \quad (8)$$

The specific steps of the multi- K nearest neighbor regression algorithm based on $l_{2,1}$ norm regularization penalty are as follows:

- (1) Normalize the input sample data
- (2) Measure and calculate the training sample data to get the best k value
- (3) Based on the k value obtained in step (2), the test sample data are measured to obtain the estimated value of the missing sample, thereby realizing the reconstruction of the missing data

3.2. The Realization of Personalized Recommendation of English Teaching Resources. Based on the reconstruction results of missing data, the following focuses on considering the path interest of student users from two aspects: browsing path selection and access time. At the same time, a Web access matrix is established for data mining and clustering, to complete the personalized recommendation of English teaching resources [11].

Assume that C represents the entire set of website sessions, and V represents the set of all browsed sub-paths [12]. Assuming that there are $v \in V$, $c \in C$, and ϑ representing the sequence of browsing pages, then the calculation formula for students' choice of interest is as follows:

$$\vartheta_k = \sqrt{\frac{\sum_{i=1}^m \sum_{j=1}^n [v_{ij} + c_{ij}]^2}{M_k}}. \quad (9)$$

Here, v_{ij} represents interest similarity; c_{ij} represents a collection of Web pages sorted by interest; and M_k represents the threshold of interest.

The visit time interest degree mainly refers to the user's interest in the time that the user stays on the page. Generally, the longer a user page stays, the more interested the user is in the page; otherwise, the user is interested in this page. The page has no interest, which results in user interest. The formula for calculating interest in visiting time is as follows:

$$E_k = \log_2 \sum_{k=1}^n T_k^2. \quad (10)$$

Here, T_k^2 represents the time that the user stays on the page.

Comprehensively the interest degree and the visit time interest degree are considered, and the two are combined to form the path interest degree. The calculation formula is as follows:

$$F(k) = \vartheta_k + E_k, \quad k = 1, 2, \dots, N. \quad (11)$$

When clustering a large number of English teaching resources, it is necessary to measure the similarity between resources and users [13]. Among them, the user path interest degree is represented by matrix U , and the specification of matrix U is set to $M \times N$, and then, the corresponding user path interest degree matrix is as follows:

$$U_{M \times N} = \begin{bmatrix} u_{11} & \cdots & u_{1n} \\ \vdots & \ddots & \vdots \\ u_{m1} & \cdots & u_{mn} \end{bmatrix}. \quad (12)$$

Assuming that user α and user β have a high degree of similarity, the similarity calculation formula between the two users is as follows:

$$\text{sim}(\alpha, \beta) = \cos(\alpha_i, \beta_i) = \frac{\alpha_i^T \beta_i}{\|\alpha_i\| \times \|\beta_i\|}. \quad (13)$$

In the process of personalized recommendation of English teaching resources, it is necessary to obtain a few

matrices first, and the matrix does not contain items that have not been accessed, the user's interest in multiple items [14] is calculated, and Q is set to represent the return value. One factor is as follows:

$$Q^{(K+1)} = A^{(K)} = [F(A^{(K)})]^{-1} F(A^{(K)}). \quad (14)$$

Here, $F(A^{(K)})$ represents the region of interest.

Various types of interest values are predicted and sorted them in combination with predicted values. The higher the predicted value, the higher the degree of interest, that is, the higher the degree of recommendation. The system extracts the highest part of the item and recommends it to students. In this way, personalized recommendation of English teaching resources is realized [15].

4. Experimental Design

To compare and test the performance of the personalized English teaching resource recommendation system based on the multi- K nearest neighbor regression algorithm proposed in this study, it is compared with the online learning resource recommendation method based on ontology and recurrent neural network, the online learning resource recommendation model based on the multi-objective optimization strategy, and the personalized learning resource recommendation method based on three-dimensional feature collaborative domination. To eliminate the influence of nearest neighbor size on the results, five nearest neighbor sizes are selected: 4, 8, 12, 16, and 20. The error caused by data division is reduced by randomly dividing the data set for many times and repeating the experiment.

We have set up an IoT sensing cluster with default configurations. The C/C++ network is used to build the related graphical model of vocal art expression and body noise. The message link model and control of the wireless sensing vocal music node are also built on the same configuration. The node transmission data simulation time is 100s with the SNR being 3 dB.

4.1. Experimental Data Set. To verify the effectiveness of the personalized recommendation system for English teaching resources based on the multi- K nearest neighbor regression algorithm proposed in this study, the three benchmark data sets in the recommendation field, the CNKI data set, the FirstSearch data set, and the IEEE Xplore data set, were carried out. For the experiment, the description of these three data sets is shown in Table 1.

First, the CNKI data set and FirstSearch data set are preprocessed. For the CNKI data set, the threshold is set to 80, that is, to retain at least 80 users who have scored, so a score matrix containing 5987 users is obtained, and then, each score value is converted to between 1 and 5. For the FirstSearch data set, the threshold is set to 300; that is, at least 300 followers are retained to score, so a scoring matrix containing 6917 followers and 1305 followers is obtained.

TABLE 1: Experimental data set.

Data set	Score value	Describe
CNKI	1~5	1675 users with 100010 ratings
FirstSearch	-10~10	73,654 users with 12,579,643 ratings
IEEE Xplore	1 or -1	23,651,458 followers, 23,574,125 ratings

4.2. Use Case Testing. Based on the abovementioned experimental data set, the system designed in this study is first tested with use cases, and the results are shown in Tables 2 and 3. Among them, the recommended examples of homepage teaching resources are shown in Table 2.

Recommended examples of teaching resource detailed pages are shown in Table 3.

According to the test cases shown in Tables 2 and 3, whether it is the recommendation of teaching resources on the home page or the recommendation of teaching resources on the detailed page, the system designed in this study can realize the recommendation function and meet the needs of users for resource recommendation, which shows that the system can meet the needs of users and is effective.

4.3. System Performance Test. To further verify the application value of the design in this article, testing its system performance is continued.

4.3.1. MAE. To verify the accuracy of the system recommendation designed in this study, firstly the general evaluation standard MAE is used to compare its recommendation effect with the traditional method. The experimental comparison results of different methods are shown in Figure 5.

Since the smaller the MAE value, the higher the recommended accuracy, and vice versa, the lower the recommended accuracy. It can be seen from Figure 5 that compared with the traditional method, the MAE value of the system designed in this study is relatively small, indicating that the recommended accuracy of the system designed in this study is higher, and it verifies the accuracy of the recommended system designed in this study. As the number of iterations continues to increase, the MAE value of the design system in this study continues to decrease, and the recommendation accuracy is gradually improved, which verifies that the design system in this study improves the quality of resource recommendations.

To choose the best K value, we use the cross-validation framework to check whether a K is the most suitable parameter, and the result is shown in Table 4.

As shown in Table 4, the K should be 5, so that we can get the best performance.

4.3.2. Precision and Recall. To continue to verify the recommended accuracy of the system designed in this study, the precision and recall evaluation criteria are used to conduct comparative experiments on different methods. The accuracy rate is for our prediction results. It indicates how many of the predicted positive samples are really positive samples.

TABLE 2: Recommended use cases for homepage teaching resources.

Use case name	Homepage teaching resource recommendation
Use case description	After logging into the system, users browse the personalized recommendation home page of teaching resources. The system recommends teaching resources that users may be interested in according to user habits and teaching resource attributes
Precondition	User login succeeded
End condition	The recommended list of teaching resources is displayed on the homepage of personalized recommendation of teaching resources
Input content	Nothing
Output content	The list of recommended teaching resources is displayed on the personalized recommendation home page of teaching resources

TABLE 3: Recommended use cases for the detailed pages of teaching resources.

Use case name	Homepage teaching resource recommendation
Use case description	After logging into the system, the user browses the detailed page of a teaching resource. The system recommends the teaching resources that the user may like according to the currently browsed teaching resources, user habits, and the attributes of teaching resources in the system
Precondition	User login succeeded
End condition	The recommended list of teaching resources is displayed on the teaching resource detailed page
Input content	Nothing
Output content	The list of recommended teaching resources is displayed on the teaching resource detailed page

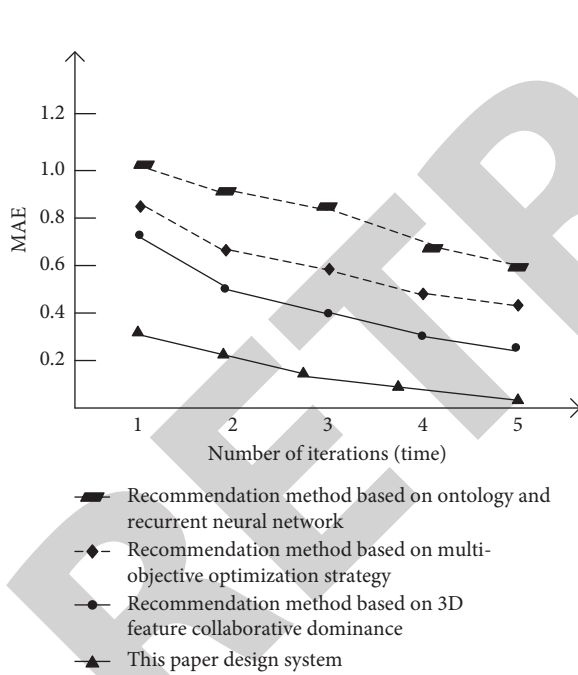


FIGURE 5: MAE comparison results of different methods.

TABLE 4: MAE comparison results of different K values.

K	1	2	3	4	5	8	10
MAE	0.35	0.38	0.29	0.26	0.10	0.14	0.22

Then, there are two possibilities for positive prediction. One is to predict the positive class as the positive class (TP), and the other is to predict the negative class as the positive class (FP), that is:

$$T = \frac{TP}{TP + FP}, \quad (15)$$

The recall rate is for our original sample. It indicates how many positive examples in the sample are predicted correctly. There are also two possibilities. One is to predict the original positive class as a positive class (TP), and the other is to predict the original positive class as a negative class (FN).

$$R = \frac{TP}{TP + FN}. \quad (16)$$

The experimental results are shown in Figures 6 and 7.

The higher the precision value, the more accurate the recommended result is. As can be seen from Figure 6, with the increase in iteration times, the precision values of different methods have increased. However, through comparison, it can be seen that the precision value of the system designed in this study is always higher than that of the traditional methods, with the highest precision value of 0.75 and the lowest value of 0.44, which is significantly higher than that of the traditional methods. It shows that the design method in this study can recommend the resources closest to the user's needs to the user according to the user's needs.

The higher the recall value, the more accurate the recommendation result. As can be seen from Figure 7, similar to the change in precision value, the recall value of different methods also increases with the increase in iteration times. The recall value of the system designed in this study is always higher than that of traditional methods.

A comprehensive analysis of the above experimental results shows that the resource recommendation accuracy of the system designed in this study is higher, indicating that its recommendation effect is better. This is because the system has designed the teaching resource detailed page recommendation module in the design. The module can

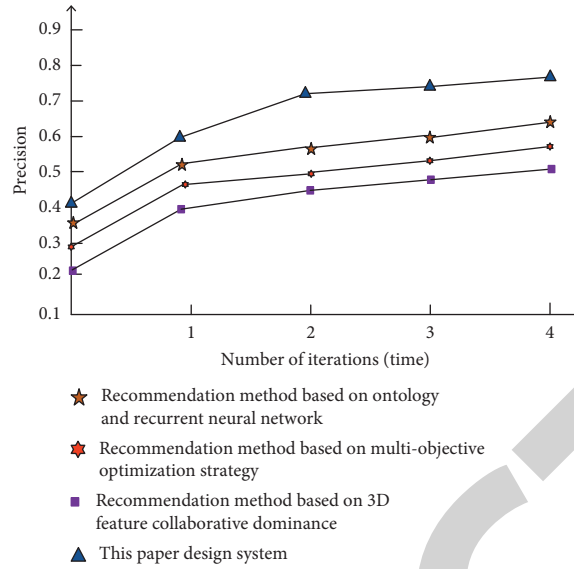


FIGURE 6: Precision comparison results of different methods.

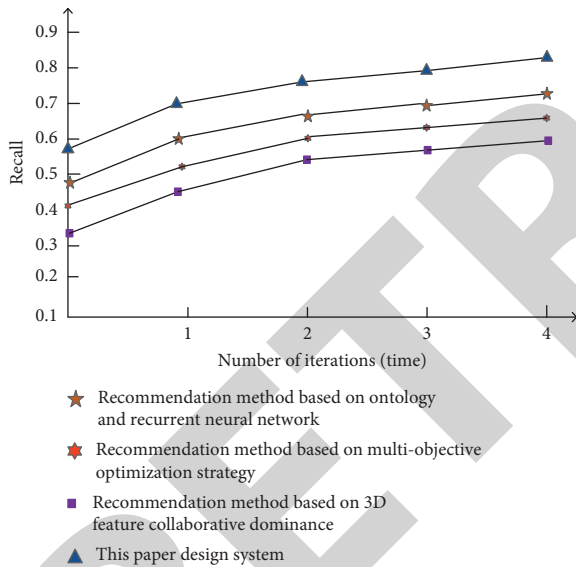


FIGURE 7: Recall comparison results of different methods.

recommend resources similar to the currently browsed teaching resources according to the teaching resources currently browsed by student users, the past teaching resource preferences of current student users, and the attributes of teaching resources in the current system, to improve the accuracy of resource recommendation.

4.3.3. Data Loss Rate (%). Due to frequent problems such as node collision and network congestion in the network, it is easy to have high data loss rate in a short time, which will have a certain negative impact on resource recommendation. Therefore, this study takes the data loss rate as the evaluation index to compare the application effects of different methods. The results are shown in Table 4.

Analyzing the data in Table 4, it can be seen that the highest value of the data loss rate in the resource recommendation of the system designed in this study is only 1.18%, and the minimum value is only 0.83%; the highest value of the data loss rate of the recommended method based on the ontology and recurrent neural network is 4.13%, and the minimum value is 2.30%; the highest data loss rate of the recommended method based on the multi-objective optimization strategy is 6.45%, and the minimum value is 3.36%; and the highest data loss rate of the recommended method based on three-dimensional feature collaborative dominance is 5.64%, and the minimum value is 4.03%. Through the above data comparison, it can be seen that the data loss rate of the system designed in this study is lower, indicating that it can retain most of the useful resources in the resource recommendation, and the recommendation result is more comprehensive. This is because the design system in this study is based on the basic idea of the multi-K nearest neighbor regression algorithm and proposes a reconstruction algorithm for missing data of English teaching resources, which reduces the data loss rate.

4.3.4. Resource Recommendation Time (s). Table 5 is used to give the time-consuming comparison results of different methods of resource recommendation. The comparison results of resource recommendation time-consuming of different methods are shown in Table 6.

Analyzing the experimental data in Table 5, it can be seen that the resource recommendation time of the designed system in this study is significantly lower than that of the traditional method. The longest resource recommendation time is only 5.36 s, while the maximum resource recommendation time consumption of the three traditional methods is 8.11 s., 11.45 s, and 12.05 s. It can be seen that the recommendation of the system designed in this study takes less time, the recommendation efficiency is higher, and it can recommend more English teaching resources for users in a

TABLE 5: Comparison results of data loss rate.

Number of iterations/time	This study design system	Data loss rate/(%)		
		Recommendation method based on ontology and recurrent neural network	Recommendation method based on the multiobjective optimization strategy	Recommendation method based on 3D feature collaborative dominance
1	0.83	2.30	3.36	4.03
2	0.87	2.41	3.42	4.12
3	0.91	2.55	4.15	4.34
4	0.94	3.22	4.35	4.50
5	0.97	3.34	4.74	4.67
6	1.10	3.50	5.63	4.89
7	1.12	3.63	5.75	5.01
8	1.15	3.74	6.15	5.27
9	1.17	4.11	6.33	5.31
10	1.18	4.13	6.45	5.64

TABLE 6: Comparison results of resource recommendation time-consuming of different methods.

Number of iterations/time	This study design system	Recommended time/(s)		
		Recommendation method based on ontology and recurrent neural network	Recommendation method based on the multi-objective optimization strategy	Recommendation method based on 3D feature collaborative dominance
1	2.36	4.22	9.36	8.75
2	2.77	4.41	9.42	8.93
3	3.52	5.25	9.55	9.04
4	3.55	5.62	9.85	9.27
5	4.11	6.14	9.94	9.63
6	4.25	6.20	10.63	9.90
7	4.33	6.63	10.75	10.28
8	4.74	6.74	11.15	11.39
9	4.74	7.11	11.33	11.47
10	5.36	8.11	11.45	12.05

shorter time. The system designed in this study can greatly improve the operating efficiency of the entire system according to the students' own interests.

5. Conclusion

In the network resource learning system, different network learners have different requirements for resources and their own hobbies, and non-personalized recommendation is no longer favored by learners. In contrast, personalized services can better meet the interests and preferences of different users. By actively interacting with users, they can stimulate their interest in learning, thereby improving the quality of learning. In this context, this study designs a personalized recommendation system for English teaching resources based on the multi- K nearest neighbor regression algorithm. The system contains five different functions: resource collection, resource sorting and classification, resource utilization, statistical analysis, and system management. Based on the basic idea of the multi- K nearest neighbor regression algorithm, a missing data reconstruction algorithm of English teaching resources is proposed, which is used to reduce the data loss rate. The system realizes accurate recommendation of the homepage and detailed page of teaching resources through the design of various functional modules, reduces the data loss rate in the recommendation process,

and improves the efficiency of resource recommendation. Through the experimental comparison results, it can be seen that the application effect of the design system in this study is obviously better than that of the traditional method, indicating that the system has higher application value.

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 no conflicts of interest.

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