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Research Article

Research on Personalized Recommendation Method of Intangible Social Heritage and Materials in Schools under Double Reduction Policy

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Individualized recommendation of imperceptible social heritage and materials in schools under the double reduction policy is to evaluate and judge students' learning interests and specialties and recommend suitable imperceptible social heritage and materials to students. Aiming at the problem that the collaborative filtering recommendation method does not match the individualized needs of primary and secondary school students under the double reduction policy, in this paper, we suggest a personalized recommendation system of imperceptible social heritage and materials in schools under the double reduction policy based on joint template feature matching and interest feature point mining. First, taking the information management platform of imperceptible social heritage and materials in schools as the structural model, the grading model and homomorphic distribution attribute model of imperceptible social heritage and materials for primary and secondary school students under the double reduction policy are constructed. Second, the probability density characteristic analysis method of joint template matching is used to construct the personalized recommendation model of the imperceptible social heritage and materials in schools. Third, then the personalized characteristic distribution and fitness parameter extraction of the imperceptible social heritage and materials in schools under the double reduction policy are carried out, so as to realize the reasonable matching of personalized characteristic requirements and project interest points and realize the personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy. Finally, a simulation experiment was carried out to test and evaluate the outcomes. The outcomes express that the personalized recommendation items of imperceptible social heritage and materials in schools with this method have higher scores, and the average absolute error and root mean square error are smaller, which improves the quality of dynamic and accurate matching between imperceptible social heritage and materials and students' hobby characteristics.

1. Introduction

The implementation of the policy of "double reduction" in education is the main way to implement our party's and government's educational policies. The improvement of school education quality and the healthy development of middle school students is also an important opportunity for the deepening of school education reform. Therefore, in the classroom teaching of rural junior middle schools, it is necessary to actively implement the "double reduction" policy and pay attention to the all-round development of students and their growth and development needs. Through the improvement of teaching quality inside the school and the standardization of training institutions outside the school, the efficient teaching can be realized, and at the same time, the learning burden of students can be reduced. Under the double reduction policy, people pay attention to how to carry forward Chinese cultural traditions and improve the learning quality of primary and secondary school students.

In fact, this is of prodigious importance to build a personalized recommendation model of imperceptible social heritage and materials in schools and to develop and design a personalized recommendation model of imperceptible social heritage and materials in schools under the double reduction policy, which will improve the push degree of imperceptible social heritage and materials in schools. Furthermore, it will also improve and progress the audience and teaching quality level of imperceptible social heritage and materials in schools. This should be noted that it is of prodigious importance to examine and investigate the personalized recommendation model of imperceptible social heritage and materials in schools under the double reduction policy of primary and secondary school students.

Individualized recommendation of imperceptible social heritage and materials in schools under the double reduction policy is based on the matching relationship between the individualized characteristics of primary, as well as, the secondary school pupils under the policy of double reduction. Moreover, by browsing and evaluating the prior information of school learners under the policy of double reduction, the individualized needs are formulated, and the resource distribution structure of imperceptible social heritage and materials and the needs of primary, as well as, the secondary institute pupils under the policy of double reduction are comprehensively considered. In fact, the personalized service items are formulated to realize information push and web page recommendations, which lays the foundation for a more efficient network experience. At the moment, the usual and classical personalized recommendation approaches predominantly include the collaborative filtering recommendation method, as suggested in Ref. [1], the recommendation method based on meta-path attention mechanism, and the recommendation model of penetration path based on reinforcement learning [2].

However, with the increase of the scale of imperceptible social heritage and materials in schools and the diversified growth of primary, as well as, the secondary college students' information under the policy of double reduction, the accuracy of recommendation is not high, while the matching degree of collaborative filtering recommendation method to the individualized needs of school scholars under the policy of double reduction is also not high. Therefore, in order to solve the inadequacies of classical and old style approaches, in this paper, we suggest a personalized recommendation algorithm of imperceptible social heritage and materials in schools under the double reduction policy based on joint template feature matching and interest feature mining. First, taking the information management platform of imperceptible social heritage and materials in schools as the structural model, the grading model and homomorphic distribution attribute model of imperceptible social heritage and materials for primary and secondary school students under the double reduction policy are constructed.

The probability density characteristic analysis method of joint template matching is used to construct the personalized recommendation model of the imperceptible social heritage and materials in schools, and then the personalized characteristic distribution and fitness parameter extraction of the imperceptible social heritage and materials in schools under the double reduction policy are carried out, so as to realize the reasonable matching of personalized characteristic requirements and project interest points and realize the personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy. Finally, the performance test through simulation experiment shows the superiority of this method in improving recommendation quality. The fundamental contributions of the work presented in this paper are as follows:

(i) In this paper, we suggest a personalized recommendation procedure under the double reduction policy based on joint template feature matching and interest feature point mining.

(ii) Taking the information management platform as the structural model, the grading model and homomorphic distribution attribute model of imperceptible social heritage and materials under the double reduction policy are constructed.

(iii) The probability density characteristic analysis method of joint template matching is used to construct the personalized recommendation model.

(iv) The personalized characteristic distribution and fitness parameter extraction of the imperceptible social heritage and materials under the double reduction policy are carried out, so as to realize the reasonable matching of personalized characteristic requirements and project interest points under the double reduction policy.

The remaining part of the manuscript is structured as discussed in the subsequent statements. The model building and information preprocessing are presented in Section 2. The suggested algorithm for optimization and its implementation is debated in Section 3. Analysis of investigational outcomes and conversation is given in Section 4. To conclude, Section 5 completes this study and discusses several guidelines and recommendations for future research.

2. Model Building and Information Preprocessing

2.1. Distribution Structure Model and Recommendation Rules of Cultural Materials of Imperceptible Social Heritage. The collaborative recommendation technology deliberated in this paper is founded on the information management platform model of imperceptible social heritage in schools. The information management platform of imperceptible social heritage in schools is a network composed of the matching relationship of all primary and secondary school students' personalized characteristics in the distribution network of imperceptible social heritage, which is abstracted into the trust communication mechanism of the network through the relationship between primary and secondary school students under the double reduction policy. Considering the trust model and confidence of network nodes, the project attribute classification and subject matching are carried out. According to the multi-agent negotiation mechanism, the trusted nodes are located and the trust degree of primary and secondary school students is analyzed under the double reduction policy. Thus, the overall structure model of personalized recommendation of imperceptible social heritage and materials in schools is obtained as shown in Figure 1.

According to the overall design of personalized recommendation model of schools' imperceptible social heritage and materials under the double reduction policy, the information management platform of schools' imperceptible social heritage and materials will integrate the trust and interest features of primary and secondary school students under the double reduction policy, build a network structure model, and carry out the feature retrieval of college students' information under the policy of double reduction. Moreover, the trust relationship model of university scholars under the double reduction policy in the information management platform of schools' imperceptible social heritage and materials is expressed in the form of the following undirected graph model [3, 4]: $G=(V, E, C)$. In which, V represents the node set of collaborative filtering of the information management platform of imperceptible social heritage in schools, and each node represents the individual primary and secondary school students under the double reduction policy in the network; E represents the set of edges, representing the correlation recommended by friends of social networks, and the correlation characteristics existing between two individuals; indicates the weight value of $C = \{c_{uv}\}$ edge. The greater the weight, the higher the trust, and the better the accuracy of the recommendation [5, 6].

Assuming that the edges in the information management platform diagram of imperceptible social heritage in schools are directed and the network diagram is directed, in the personalized recommendation system of imperceptible social heritage in schools under the double reduction policy, $\{u_1, \ldots, u_N\}$ stands for the set of elementary and secondary school students under the double reduction policy, $\{v_1, \ldots, v_M\}$ stands for the set of untrustworthy nodes, and $R = [R_{u,v}]_{N\times M}$ stands for the score matrix of primary and secondary school students under the double reduction policy, where $R_{u,v}$ stands for the evaluation of primary and secondary school students' attribute interest in item V under the double reduction policy under the constraint of association rules. $R_{u,v}$ can be any real number. In social networks, the scores of primary and secondary school students can reasonably reflect the quality of the recommended model under the double reduction policy determined by data sparsity [5]. Therefore, it is not uncommon to use the scoring mechanism to evaluate the quality of the recommended model. In this paper, the scoring interval of students is set to [0, 1]. By using the scoring method of primary, as well as, the secondary college students' items under the policy of double reduction, the semantic features of school and college students' items under each double reduction policy are expressed as: the correlation matching degree of network distribution units to nodes is expressed, and its values range from [0, 1], with 0 indicating complete mismatch and 1 indicating complete matching.

According to the trust model and recommendation rules of the information management platform of imperceptible social heritage in schools set above, the density expression of characteristic probability function of primary and secondary school students' trust evaluation under the double reduction policy is obtained as follows in equation (1):

$$p(y|\alpha, \theta) = \sum_{k=1}^{K} \alpha_k p_k \left(y \mid \mu_k, \sum_k \right). \tag{1}$$

The feature vector retrieval technology [7, 8] to search the prior feature information of school students under the policy of double reduction in the feature space of mutual trust is used, the key information retrieval vector model of primary and secondary school students' interests and hobbies under the double reduction policy in the retrieval area is given by equation (2):

$$\Delta d = \frac{1}{2} \times t \times u \times \sum_{i=1}^{t} \sum_{j=1}^{u} \left\| \bar{d}_i - \mathrm{M}\hat{d}_i^{j} \right\|^2. \tag{2}$$

The semantic concept tree [9] and analysis of the binary relationship between student object and item attribute set in the information management platform of imperceptible social heritage in schools are constructed. The binary feature tree [10] $K=(O, a, r)$ to describe the information distribution list of personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy is constructed, where o is the collection of primary and secondary school students' objects under the policy and strategy of double reduction, a is the collection of items to be recommended in the information management platform of imperceptible social heritage and materials in schools, and r is a binary relationship between o and a. The spatial dimension of the prediction score of personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy is set as M. Through the evaluation of personalized characteristics of primary and secondary school students' interests under the double reduction policy, the correlation degree between primary and secondary school students' behaviors and preferences under the double reduction policy is obtained as follows in equation (3):

$$x_t = \mathrm{MSF}(t) \sum_{k\in K_t} \beta_{t,k}. \tag{3}$$

Based on the analysis of the correlation between behavior and preferences, the scores of school pupils under the strategy of double reduction are mapped to the [0, 1] interval, and the prediction model of primary, as well as, the secondary school students' scores under the strategy and policy of double reduction of the recommended model is constructed.

2.2. Construction of Personalized Recommendation Model of Imperceptible Social Heritage and Materials in Schools. Using the probability density characteristic analysis method [11, 12] of joint template matching, the personalized

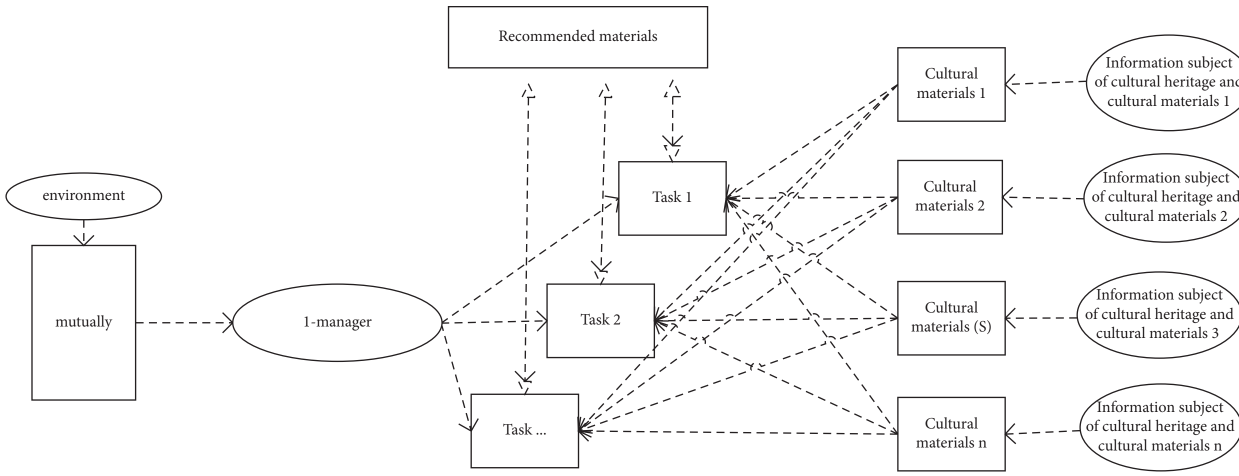

Figure 1: Overall structure model of personalized recommendation of imperceptible social heritage and materials in schools.

recommendation model of imperceptible social heritage and materials in schools is constructed. The conditional probability formula of the trust degree of any two items X and Y recommended to primary and secondary school students under the social double reduction policy is as follows in Equations (4) to (6):

$$\text{WebJaccar d}(X, Y) = \frac{P(X \cap Y)}{P(X) + P(Y) - P(X \cap Y)}, \tag{4}$$

$$\text{WebOverlap}(X, Y) = \frac{P(X \cap Y)}{\min\left(P(X), P(Y)\right)}, \tag{5}$$

$$\text{WebDice}(X, Y) = \frac{2P(X \cap Y)}{P(X) + P(Y)}, \tag{6}$$

where $P(X)$ and $P(Y)$ are the comprehensive weights of the imperceptible social heritage cultural recommendations of projects X and Y, respectively, and are joint conditional probability density functions, which represent the distribution weights of the accurate scores of imperceptible social heritage cultural recommendations of projects X and Y in the [0, 1] interval. Revise each vector v_i, and the process of predicting and scoring all items is represented by vi, that is $v_i = ((w_1, t_1), (w_2, t_2), \ldots (w_m, t_m))$. To calculate the central vector $C(Y)$ of each personalized feature distribution in the information management platform of imperceptible social heritage in schools, the formula for calculating the trust degree of X and Y is mathematically illustrated in Equation (7):

$$\text{Sim}(X, Y) = \text{Cos}(X, Y) = \frac{C(X) \cdot C(Y)}{|C(X)| \cdot |C(Y)|}. \tag{7}$$

Ignore the link structure information of the cultural materials of imperceptible social heritage in schools, and conduct information retrieval according to the differentiated characteristics of primary and secondary school students' prior keyword semantic information w_1 and w_2 under the double reduction policy. The effective value of the retrieval is $\text{di s}(w_1, w_2)$, which indicates the degree of understanding and acceptance of students in the cultural materials of imperceptible social heritage in schools.

The revised weights of the personalized recommendation model of the imperceptible social heritage and materials in schools of all neighboring nodes $v \in N_u$ established are mathematically expressed in equation (8):

$$\overline{R}_{ik} = \sum_{j \in N_u} C^*_{i,j} R_{jk}, \tag{8}$$

where $\overline{R}_{ik}$ represents the direct trust of primary and secondary school students' u_i to project v_j under the double reduction policy, R_{jk} represents the extracted value of interest characteristics of primary and secondary school students' u_j to the overall structural information of project v_k under the double reduction policy, and $C^*_{i,j}$ is a modified weighted vector. Then, the predicted score of primary and secondary school students' U to semantic information retrieval under the double reduction policy in the information management platform of imperceptible social heritage in schools can be expressed as follows in equation (9):

$$\begin{pmatrix} \overline{R}_{i,1} \\ \overline{R}_{i,2} \\ \cdots \\ \overline{R}_{i,m} \end{pmatrix} = \begin{pmatrix} R_{1,1} & R_{2,1} & \cdots & R_{n,1} \\ R_{2,1} & R_{2,2} & \cdots & R_{n,2} \\ \cdots & \cdots & \cdots & \cdots \\ R_{1,K} & R_{2,K} & \cdots & R_{n,m} \end{pmatrix} \begin{pmatrix} C^*_{i,1} \\ C^*_{i,2} \\ \cdots \\ C^*_{i,n} \end{pmatrix}. \tag{9}$$

According to the actual situation of the collaborative filtering system, combined with the behavior characteristics and interest distribution of primary and secondary school students under the double reduction policy, the recommendation model is constructed.

3. Algorithm Optimization Implementation

3.1. Question and Personalized Characteristics Analysis. On the basis of the design of the network structure model and the construction of recommendation rules, the optimization design of the collaborative filtering algorithm [13] is carried out. In this paper, a personalized recommendation algorithm of schools' imperceptible social heritage and materials based on the double reduction policy of joint templating feature matching [14] and interest feature mining [15] is proposed, and the personalized recommendation model of schools' imperceptible social heritage and materials is constructed by using the probability density feature analysis method of joint templating matching. The personalized feature distribution and fitness parameter extraction of the imperceptible social heritage and materials in schools under the double reduction policy are carried out. Based on the recommendation constraint model of credibility, the fuzzy distribution matrix C_{kv}^* of personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy is constructed according to the revised weights. Therefore, for the recommended items, the trust matrix satisfies the constraint as given in equation (10):

$$\overline{R} = TR. \tag{10}$$

In the joint recommendation of student a to primary, as well as, the secondary school students' neighbor node B under the strategy and policy of double reduction, the conditional probability of primary, as well as, the college and secondary school students' scoring under the strategy of double reduction is expressed as follows in equation (11):

$$p\left(R \mid U, V, \sigma_R^2\right) = \prod_{i=1}^{n}\prod_{j=1}^{m}\left[N\left(R_{ij} \mid g\left(U_i^T V_j\right), \sigma_R^2\right)\right]^{I_{ij}^R}, \tag{11}$$

where $N(x \mid \mu, \sigma^2)$ indicates that the item characteristic distribution variable x obeys a standard normal distribution with mathematical expectation μ and standard variance σ^2, and $I_{ij}^R$is a sparse indicator function. If the primary and secondary school students' u_i have personalized demand for items v_j under the double reduction policy, the score indicator is 1; otherwise, the score indicator is 0, thus completing the personalized characteristic analysis of primary and secondary school students under the double reduction policy [16].

3.2. Implementation of Personalized Recommendation Algorithm for Imperceptible Social Heritage and Materials in Schools. Taking the information management platform of imperceptible social heritage in schools as the structural model, the grading model and homomorphic distribution attribute model of imperceptible social heritage in schools under the double reduction policy are constructed [17]. Starting from the social trust network, the matching probability distribution of personalized feature demand is as follows in equation (12):

$$p\left(R \mid T, U, V, \sigma_R^2\right) = \prod_{i=1}^{n}\prod_{j=1}^{m}\left[N\left(R_{ij} \,\middle|\, g\left(\sum_{k \in N_u} w_{ik} U_k^T V_j\right), \sigma_T^2\right)\right]^{I_{ij}^R}. \tag{12}$$

Based on the analogical explanation of the recommendation of cultural materials of imperceptible social heritage in schools under the double reduction policy, the Bayesian inference [18, 19] can be used to obtain the following expression in equation (13):

$$p(y|\alpha, \theta) = \sum_{k=1}^{K} \alpha_k p_k\left(y|\mu_k, \sum_k\right). \tag{13}$$

In the mutual information area of feature space, if the scoring model and project attributes are independent of each other, the trust weight of personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy is expressed as follows in equation (14):

$$\begin{aligned} p\left(U, V \mid R, w, \sigma_w^2, \sigma_U^2, \sigma_V^2\right) &\propto p\left(R \mid w, U, V, \sigma_w^2\right) p\left(U \mid \sigma_U^2\right) p\left(V \mid \sigma_V^2\right) \\ &= \prod_{i=1}^{n}\prod_{j=1}^{m}\left[N\left(R_{ij} \,\middle|\, g\left(\sum_{k \in N_u} w_{ik} U_k^T V_j\right), \sigma_w^2\right)\right]^{I_{ij}^R} \times \prod_{i=1}^{n} N\left(U_i \mid 0, \sigma_U^2 \mathrm{I}\right) \times \prod_{J=1}^{m} N\left(U_j \mid 0, \sigma_V^2 \mathrm{I}\right). \end{aligned} \tag{14}$$

In order to achieve a reasonable match between the personalized feature requirements and the interest points of the project, considering the overall structure information in the information management platform of imperceptible social heritage in schools, through personalized feature extraction [20], the trust degree of information fusion is recorded as C_{uv}^* and is mathematically expressed in equation (15):

$$C_{uv}^* = \sqrt{\frac{d_{\mathrm{in}}(v)}{d_{\mathrm{out}}(u) + d_{\mathrm{in}}(v)}} \times C_{uv}. \tag{15}$$

The matrix decomposition technology is used to decompose the eigenvectors of primary and secondary school students' needs and recommended items under the double reduction policy [21]. The process is given by equation (16):

$$\begin{aligned} x_i(t) = &\sum_{k=1}^{p}\sum_{l=0}^{2} \varphi_{kl}\left[w_{i1}^l, \cdots, w_{in}^l\right]\left[x_1(t-k), \cdots, x_n(t-k)\right]^T \\ &- \sum_{k=1}^{q}\sum_{l=0}^{2} \theta_{kl}\left[w_{i1}^l, \cdots, w_{in}^l\right]\left[\varepsilon_1(t-k), \cdots, \varepsilon_n(t-k)\right]^T + \varepsilon_i(t). \end{aligned} \tag{16}$$

The formula will be expanded by l, therefore, leading to equation (17):

$$x_i(t) = x_i^1(t) + x_i^2(t) + x_i^3(t). \tag{17}$$

Semantic similarity of attribute [22, 23] set i_x, i_y of recommended items of imperceptible social heritage and materials in schools is as follows in equation (18):

$$JL_1 = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{\sqrt{\left(A_{iseq} - B_{jseq}\right)^2 + 1}}{\left|A_{iq} - B_{jq}\right| + 1}, \tag{18}$$

where N is the amount of nodes in this particular layer of the information management platform of imperceptible social heritage in schools, m is the modulus vector negotiated by the main body, which indicates that the weighted vector of elements in the first row is $i, i = 1, 2, \cdots, n$ and w_{i1}^{1k}'s personalized feature extraction output, B_{jseq} indicates the accurate position serial number of imperceptible social heritage in schools, and A_{iq} is the intra-cluster error, so as to realize the reasonable matching of personalized feature requirements and project interest points and realize personalized recommendation of imperceptible social heritage in schools under the double reduction policy [24].

4. Analysis of Experimental Results

During the experiment of personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy, the simulation platform is MyEclipse 8.0 which is an investigational simulation environment, and the algorithm is developed and designed by Java platform and programming language. This should be noted that the data used in all experiments come from an online website of the information management platform of imperceptible social heritage and materials in large schools in Slashdot, and these data are captured by the web crawler. The information management platform of imperceptible social heritage in schools includes 200 primary and secondary school students' comments under the double reduction policy and 399,322 sides of the double reduction policy, which is used as the prior instruction statistics set suggested by the network. Similarly, the other important and relevant parameters are: $Q = 45$, $c_1 = 122$, $c_2 = 210$, $c_r = 24$, $\mu_1 = \mu_2 =0.332$, $\rho_1 = \rho_2 =0.43$, and $\delta = 0.8$. In order to associate the benefits and drawbacks of the recommendation algorithm, in the recommendation quality evaluation, the average absolute error (MAE) and root mean square error (RMAE) are implemented in order to analyze the quality of personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy. The definitions of the two qualities are described as follows in equations (19) and (20) The MAE is defined by equation (19) given as follows:

$$MAE = \frac{\sum_{i,j}\left|r_{i,j} - \bar{r}_{i,j}\right|}{N}, \tag{19}$$

wherein, it indicates the actual scores of students interested in items in the information management platform of imperceptible social heritage in schools and indicates the predicted scores of items after personalized feature analysis by adopting the personalized recommendation model of imperceptible social heritage in schools under the double reduction policy, N is the crawling times of crawlers [25]. This should be noted that the RMSE represents the square sum of the unconventionality and deviations amongst the observed value and the true significance of primary and secondary school students' scores under the double reduction policy for the personalized recommendation of imperceptible social heritage and materials in schools. Its definition of the RMSE metrics is as follows in equation (20):

$$\text{RMSE} = \sqrt{\frac{\sum_{i,j}\left(r_{i,j} - \bar{r}_{i,j}\right)^2}{N}}. \tag{20}$$

The parameter description in the formula is the same as above. RMSE can effectively reflect the satisfaction of primary, as well as, the college and secondary school students under the strategy of double reduction in the process of personalized recommendation of imperceptible social heritage and materials in schools. According to the above-mentioned simulation environment setting and the quality evaluation index, the recommendation performance analysis is carried out, in which the number of primary and secondary school students under the double-reduction policy of grading is divided into groups, which are, respectively, set as "1~10," "11~20," "21~40," "41~80," "81 ~160," and "> 160 [26].

Figure 2 describes the fuzzy matching distribution model of schools' imperceptible social heritage and cultural data recommendation, and on this basis, it realizes the recommendation of schools' imperceptible social heritage and cultural data. It tests the average absolute error of the evaluation of schools' imperceptible social heritage and cultural data recommendation by using this algorithm and traditional recommendation algorithm and procedure. The investigation demonstrates that the MAE of this approach has the lowest value among primary and secondary school students under each grading double reduction policy, which indicates that the matching degree of personalized feature needs and project interest points is the highest. The MAE comparative experimental results are shown in Figure 3.

Figure 4 describes the comparison results of RMSE value of different methods and approaches for the personalized recommendation of imperceptible social heritage and materials in schools and colleges under the double reduction policy. Similarly, it can be concluded that the RMSE value of this method is the lowest, indicating that primary and secondary school students have the highest score and the best satisfaction with the recommendation results under this method under the double reduction policy and strategy.

5. Conclusions and Future Research

In this paper, the personalized recommendation of imperceptible social heritage and materials in schools under the policy and strategy of double reduction is studied to meet the individualized needs of primary, as well as, the colleges and secondary schools' students under the policy and strategy of double reduction and improve the quality of network

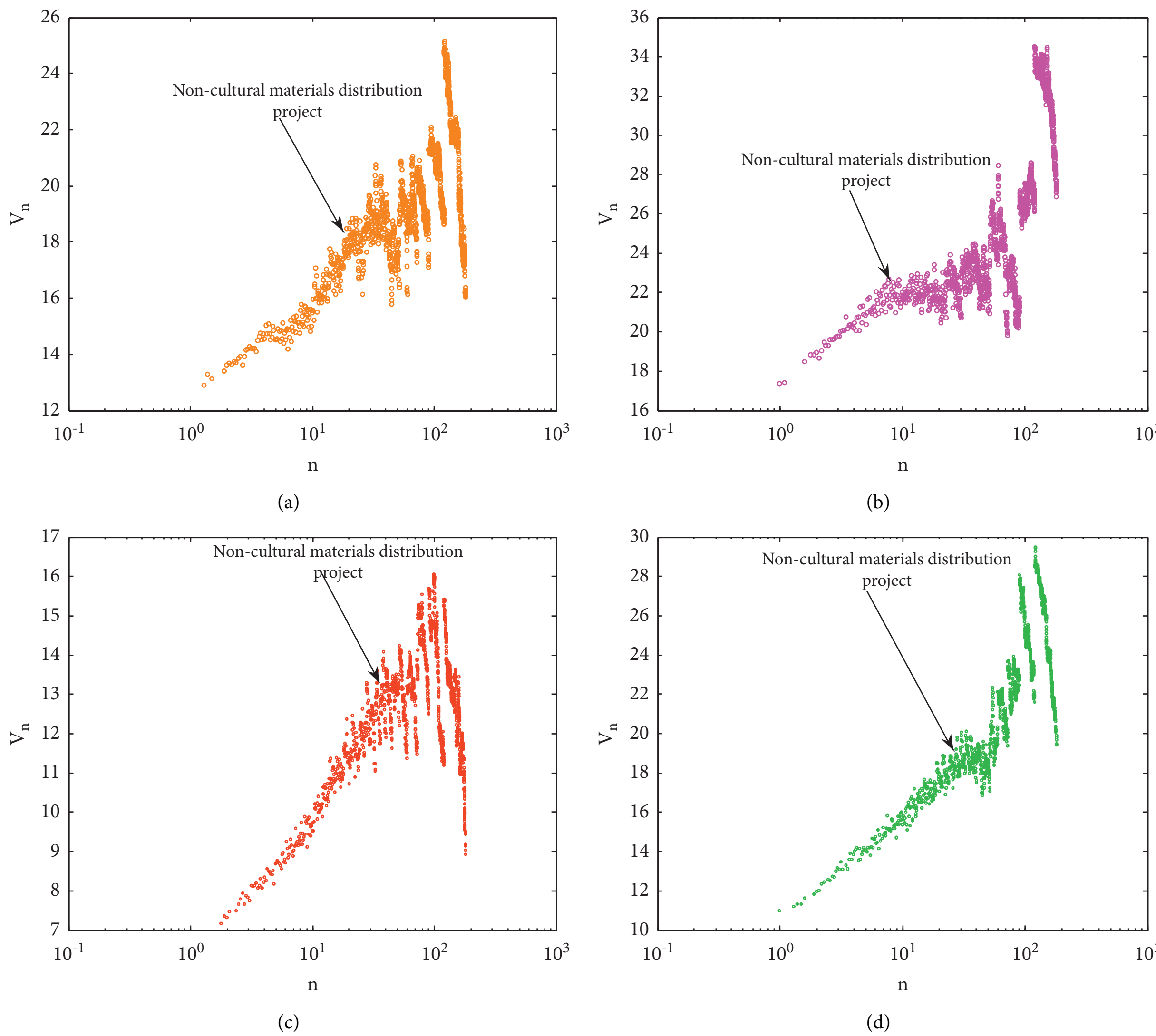

FIGURE 2: Fuzzy matching project set recommended by cultural materials of imperceptible social heritage in schools. (a) Group 1. (b) Group 2. (c) Group 3. (d) Group 4.

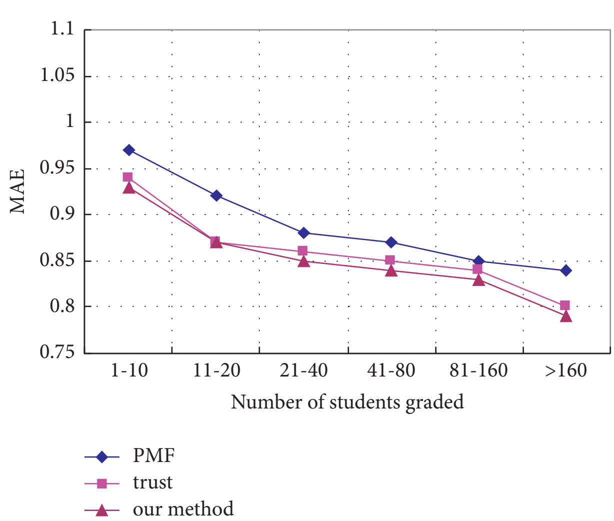

FIGURE 3: The MAE comparative experimental results.

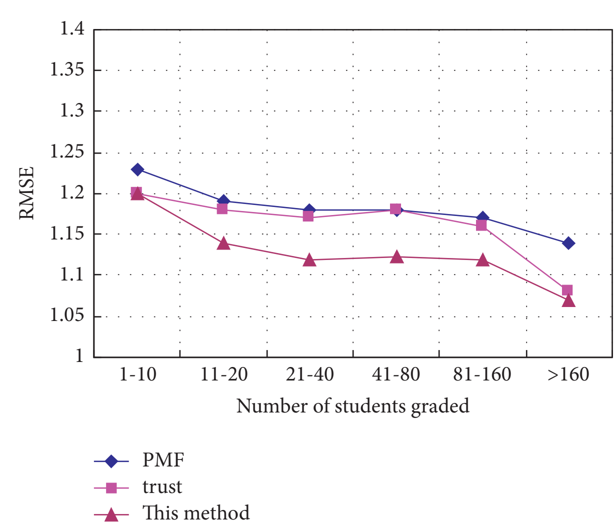

FIGURE 4: The RMSE comparative experimental results.

service. A personalized recommendation algorithm of imperceptible social heritage and materials in schools under the double reduction policy based on joint template feature matching and interest feature point mining is proposed. First, the grading model and homomorphic distribution attribute model of imperceptible social heritage and materials for primary and secondary school students under the double reduction policy are constructed by taking the information management platform of imperceptible social heritage and materials in schools as the structural model. The probability density characteristic analysis method of joint template matching is used to construct the personalized recommendation model of the imperceptible social heritage and materials in schools, and then the personalized characteristic distribution and fitness parameter extraction of the imperceptible social heritage and materials in schools under the double reduction policy are carried out, so as to realize the reasonable matching of personalized characteristic requirements and project interest points and realize the personalized recommendation of imperceptible social heritage and materials in schools under the double reduction policy.

The results show that the personalized recommendation of imperceptible social heritage and materials in schools with this method has a high score, and the average absolute error and root mean square error are small, which improves the recommendation quality of imperceptible social heritage and materials in schools and has a good application prospect. In the future, we will extend this work with a deep learning-based neural network mode. And will investigate the study of model precisions. Moreover, we will work toward proposing an updated version of the proposed algorithm, where, machine learning methods should be used to enhance the accuracy and performance quality. Using big data, and the graph convolutional network model will definitely improve the performance of the proposed technique. The filtering task is to compute intensive and the matching time could be significantly reduced using big data analytics and edge computing model.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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