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Research Article

English Online Course Development Model and Course Content Recommendation

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The process of education informatization has been accelerated in the Internet era. English course teaching in colleges and universities also gradually follows the development of the times and makes efforts to promote the reform of informatization teaching. This paper gives the design and application strategy of the English course development model in China's colleges and universities and designs a diversified teaching model. In addition, aiming at the unreasonable selection of teaching resources and learning materials, this paper designs a multidimensional course recommendation algorithm with integrated features. The proposed algorithm uses a deep learning model for data feature extraction and extracts the information of course attributes and review texts. Then an improved association rule algorithm is conceived to perform association clustering analysis on the original course categories to increase the coverage of recommendations. Experimental results demonstrate that the proposed content recommendation algorithm can recommend high-quality course resources for English teachers, and its performance is better than other algorithms.

1. Introduction

The new round of information technology changes and the continuous innovation of learning culture have pushed education informatization into a brand new development period [1, 2]. In recent years, online curriculum construction and education model innovation in a global context have gradually received widespread attention in the field of educational theory and practice [3, 4]. It has triggered the reform of educational models and management decision patterns in the field of education and has now become a key driver for educational innovation and development. In particular, the impact of the new crown pneumonia epidemic in 2020 has made teachers and students aware of the imperative of conducting online courses [5]. In the process of English professional development and teaching reform in China's universities, schools and educators are continuously exploring the development and construction of online courses. They hope that they can use the effective integration and utilization of educational resources to promote the construction of English majors and the development of education through modern and informative educational means and to achieve innovative reforms in course teaching [6].

Online teaching of English courses in higher education is a class-based process in which English teachers organize and implement teaching activities for students by relying on the Internet, computers, and other platforms [7, 8]. The selection of teaching resources is indispensable for teachers and students. Therefore, resource recommendation on online resource education websites is crucial. Personalized course recommendation is a hot topic of research in online education, which can reduce the dropout rate of online learning and stimulate and motivate learning. According to the different recommendation methods, recommendations based on traditional methods and model-based recommendations make up the course recommendation methods.

The collaborative filtering is the most widely used, which mainly uses learner or course similarity relationships to generate recommendations [9, 10]. Due to the scoring sparsity problem, information such as interest preferences, browsing behaviors, and learning styles are usually presented to increase the accuracy of preference representation. Or mix other methods to enhance the course prediction accuracy, such as the weighted combined collaborative filtering and FP-growth algorithm in literature [11]. Content-based recommendation mainly relies on domain knowledge to match learner portraits with course portraits and thus generate recommendations. It can get rid of the over-reliance on scoring data and alleviate the cold start problem. However, its drawback is that it is highly dependent on feature engineering and prone to overspecialization [12]. In general, although simple to implement, traditional course recommendation methods have limited analysis of learners and course content and can only predict learners' shallow preferences [13–15].

The model-based recommendations are gradually favored by researchers to deeply explore the intrinsic association between learners and courses and improve recommendation satisfaction. In particular, matrix decomposition re-represents learners and resources in a low-dimensional space, which effectively compensates for the problem of low accuracy of traditional collaborative filtering recommendations [16]. The literature [17] introduces interests, needs, and suggestions from support staff to propose a learning outcomes-based course recommendation model for students to select appropriate courses. The literature [18] uses a field-aware factorization machine (FFM) to simulate a common matrix decomposition model to help users select appropriate movies. The literature [19] uses non-negative matrix decomposition (NMF) to implement topic modeling for course recommendation.

In recent years, deep learning has been providing new ideas for personalized recommendations [20–22]. Compared with matrix decomposition, which is limited to modeling linear relationships, deep learning can effectively fuse heterogeneous data from multiple sources and automatically learn deep representations of various features to further alleviate the data sparsity and cold start problems. The literature [23] combines learner attributes, browsing behavior, and course text feature to model learner interests using deep confidence networks. The literature [24] proposes a CNN-LSTM recommendation model to obtain recommendations for users by capturing contextual dependencies of user rating data and extracting locally relevant features. The literature [25] proposes a course recommendation method that combines learner suitability and course collocation. The literature [26] proposed a trust-aware course recommendation model based on trust perception. The literature [27] proposes a course recommendation method based on deep Bayesian ranking. The method uses NAIS neural network to deeply encode learner interaction record, and then applies Bayesian ranking to construct a pairwise loss function for course ranking optimization. The literature [28] addresses the shortcomings of existing deep learning methods that are difficult to handle graphically structured data and employs graph neural networks to capture the high-level implicit relationships between nodes, which in turn generates more accurate top-n course recommendations.

To explore the development of English online courses, select effective teaching resources and continuously improve students' interest in English learning, and this paper presents the significance of the design and application of the English online course development model and provides the countermeasures for model development and application. And the quality teaching resources are recommended according to the multidimensional fusion features extracted by deep learning and association algorithms. This paper gives the design and application strategy of the English course development model in China's colleges and universities and designs a diversified teaching model. In addition, aiming at the unreasonable selection of teaching resources and learning materials, this paper designs a multidimensional course recommendation algorithm with integrated features. It consists of four main parts: the first part is the introduction, the second part is methodology, the third part is result analysis and discussion, and the fourth part is the conclusion.

2. Methodology

2.1. English Online Course Development Model Significance and Requirements. The model design significance is presented in Figure 1. And the model design requirements are shown below.

Follow the objectives of professional education policy and clearly set the direction of curriculum construction: on the one hand, the online course construction should follow the goal of strengthening students' learning ability cultivation and keep moving in that direction. The online course construction should emphasize the independent learning of English students under the guidance of lecturers and realize the professional theoretical knowledge system perfection and development needs by means of the independent construction of students' knowledge. On the other hand, the online course construction should have the fundamental goal of strengthening brand advantages and enhancing the influence of English. In the development and construction of English online courses, the school should make the basic development goal of traditional teaching emphasizing practicality and online courses highlighting characteristics.

Actively build a cooperative alliance of multiple subjects and optimize the mechanism of professional collaborative development: based on the construction and development practices of foreign online courses, actively building a cooperative alliance of multiple subjects is an effective measure to promote the common construction and sharing of educational resources in English courses. The advantage of such an alliance is that the participants in the alliance have a relatively stable and long-lasting cooperation foundation, which can effectively generate a development mechanism for information sharing, cooperative alliance operation, and application promotion of English online course education resources.

Strengthen the resource environment and supporting policies to ensure the online course construction: build a scientific and perfect system, and resource guarantee

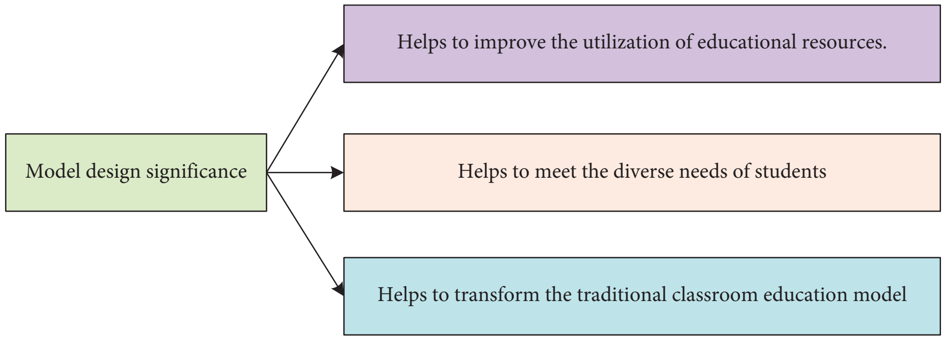

Figure 1: Model design significance.

environment. As the main body of English online course development, application, and innovation, our universities determine the quality of course resources to a large extent. This requires schools to draw up a sound protection system and regulations to strengthen resource protection.

Optimize the operation system of English education management and service in colleges and universities. The development, construction, and application of English online courses must be supported by a supporting educational management and operation mechanism to ensure the smooth promotion of course construction and application.

2.2. Model Framework. The teaching process is integrated with the resource-based teaching platform, the screen-sharing teaching platform, and the evaluation teaching platform to enrich the teaching process and make students more active in learning. In other words, some of the functions of these three platforms are used together in the teaching process. The flow chart of online teaching method is shown in Figure 2.

The English online course model explores the student-centered teaching model and builds a new relationship between teaching and learning. The specific model design is shown in Figure 3.

2.2.1. Pre-Course Introduction Phase. This phase of instruction focuses on developing students' foundational skills. Students preview the text, study the knowledge video in stages, and complete the guided learning tasks. This stage starts from theory so that students can initially have the theoretical basis and analytical ability to appreciate the text and achieve the target. The top-down approach adopted by the teacher facilitates students to verify their findings based on interpretation. The precourse introductory stage not only effectively guides students into their roles and reduces learning anxiety but also provides favorable conditions for securing classroom interaction time and improving interaction effectiveness.

2.2.2. Offline Course Phase. The focus of this stage is to enable students to acquire a certain knowledge of the language and style and then to use this knowledge proficiently. At this stage, students need to dig deeper into the text and communicate around important and difficult points. Teachers can help students observe language use directly and enhance their interest in language learning and their ability to discover language patterns on their own initiative by using a corpus. In the meantime, teachers should actively build scenarios to guide students' communication, discussion, and reporting when conducting teaching. Students' self-assessment and peer assessment are then carried out, and timely teacher feedback is provided.

2.2.3. Post-Course Intensive Phase. At this stage, teachers will assign extended learning activities for students to encourage them to use what they have learned to solve problems. At the same time, teachers can integrate the class English audio-visual practice sessions by having students work in groups to make microfilms. Teachers encourage students to use what they have learned about language and to empathize with the relationship between character and language and modal expression.

2.3. English Education Resources Recommendation. Course recommendation is a key aspect of online courses. Effective course content selection can increase students' listening rate and satisfaction. The key to course recommendation lies in pinpointing the learning goals and learning needs of students of different levels and finding the most suitable course resources. The overall framework of the multifeature fusion recommendation algorithm proposed is shown in Figure 4. The model inputs are learner interaction records, comments, and multiple attributes of the course (course category, course difficulty, and course description). In particular, association clustering analysis is applied to the course categories, and the original categories are converted into new category labels as inputs. Then learner features are modeled and course features are modeled separately. The input data are first embedded into a low-dimensional space. Then a multilevel attention mechanism is applied to capture the corresponding key features to generate learner and course hidden vectors, respectively. For interaction records and course descriptions, a bidirectional long- and short-term memory network and a text convolutional neural network are used to integrate contextual features after embedding to further enrich their semantic representations, respectively. Finally, the entire recommendation model is trained with probability matrix decomposition, and the

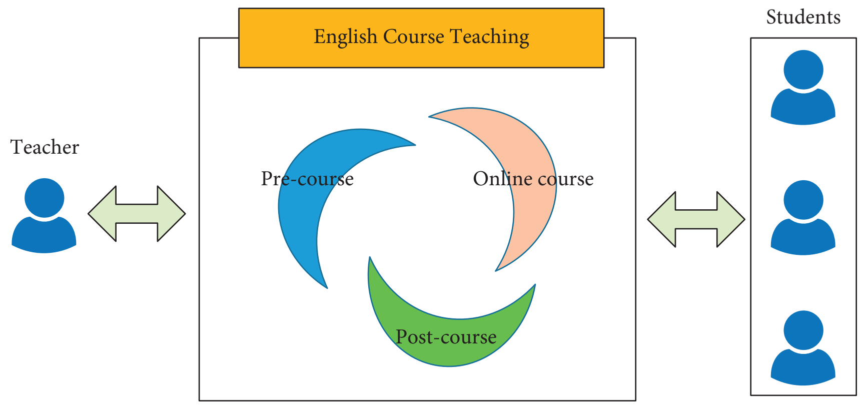

Figure 2: Flow chart of online teaching method.

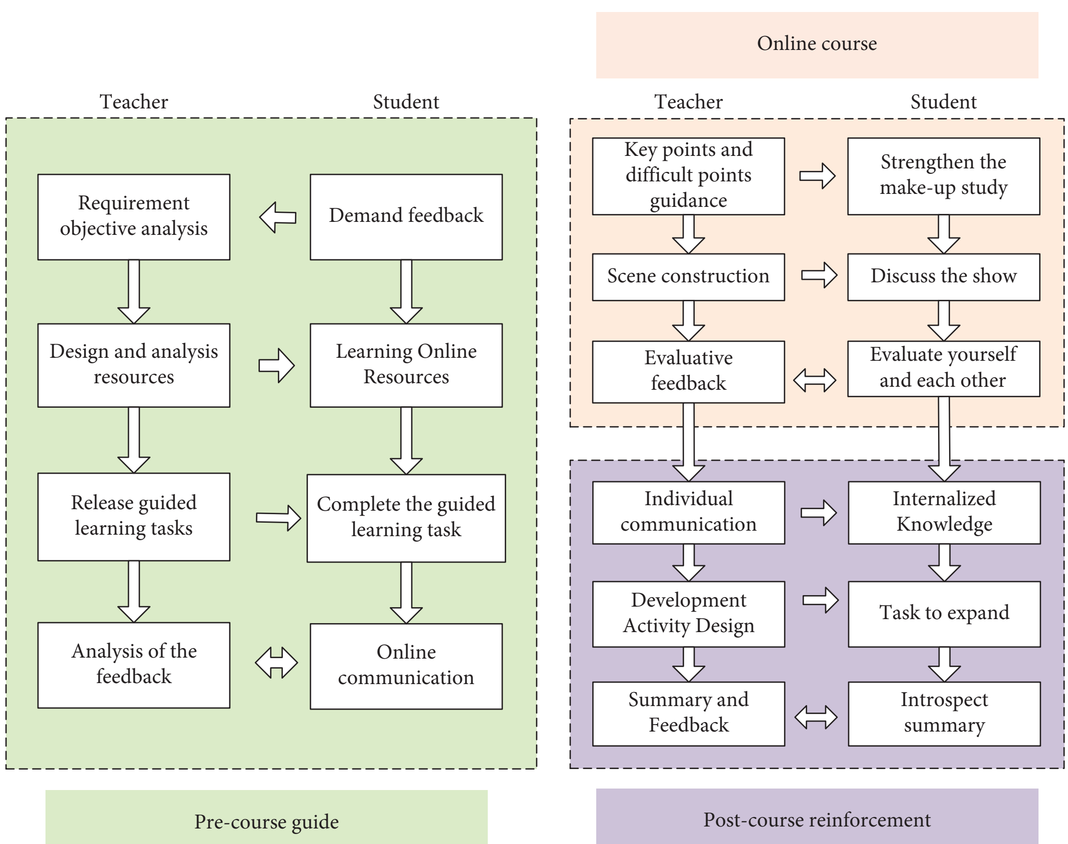

Figure 3: English online course model.

neural network parameters are continuously updated to minimize the mean squared error (MSE) value. The optimized parameters are used to determine the learner and course hidden vectors, and the inner product of the two is used to generate predicted ratings and top-n recommendations.

2.3.1. Learner Characteristics Modeling. The interaction feature extraction module uses learners' course interaction records to represent their course preference features. First, the course ids reviewed by learners are arranged in chronological order as $XR_x = \{xd_1, xd_2, \cdots, xd_t\}$. An embedding operation is performed on XR_x to obtain a low-dimensional feature vector $\mathbf{e}_l\,(l \in [1, L])$, and L is the length of the sequence.

The embedded vector $\mathbf{e}_l$ is fed into a Bidirectional Long-Short-Term Memory (Bi-LSTM) network to capture learners' dynamic course preferences. The output sequence features are represented $\overline{\mathbf{e}_l}$, as shown in.

$$\overline{\mathbf{e}_l} = Bi - LSTM\left(\mathbf{M}_1, \mathbf{h}_1, \mathbf{e}_l\right), \tag{1}$$

where $\mathbf{M}_1$ and $\mathbf{h}_1$ are all the weight and bias variables in thebi-LSTM calculation, respectively.

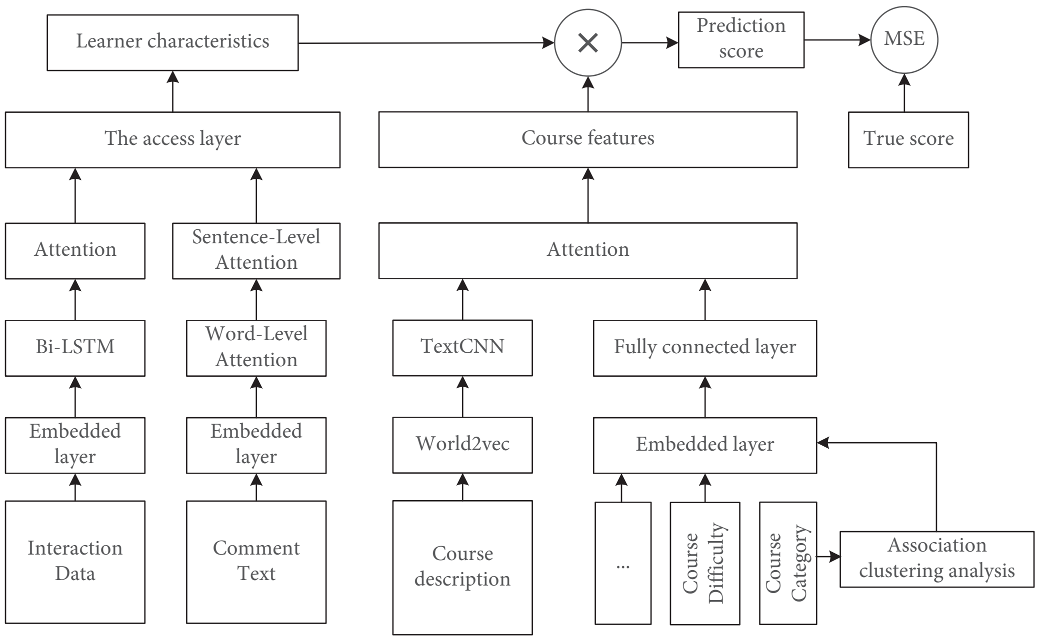

Figure 4: Multifeature fusion course recommendation framework.

Since the contribution of different courses to the representation of learner preferences varies, the attention mechanism is introduced to assign corresponding weights to the courses in the sequence. First, a nonlinear transformation of $\overline{\mathbf{e}_l}$ is performed to obtain the attention score al for each course, as shown in.

$$\mathbf{g}_l = tanh\left(\mathbf{M}_2\overline{\mathbf{e}_l} + \mathbf{h}_2\right), \tag{2}$$

where $\mathbf{M}_2$ and $\mathbf{h}_2$ are the weights and bias terms, respectively, and tan$h$ is the activation function. To ensure that the sum of attention weights is 1, the normalized attention weight $\mathbf{g_l}$ is calculated using the softmax function, as shown in.

$$g_l = \frac{\exp\left(g_l^n u_u\right)}{\sum_{l=1}^{l} \exp\left(g_l^n u_u\right)}, \tag{3}$$

where $\mathbf{u_x}$ represents the feature vector of the target course. Finally, the contextual course feature vector is weighted and summed to output the learner's course preference feature θ_p, as shown in.

$$\theta_p = \sum_{l=1}^{L} \overline{g_l e_l}. \tag{4}$$

The review feature extraction module takes the course reviews posted by learners as input and identifies key features in the reviews that express learners' preferences through word-level attention layers and sentence-level attention layers.

The word-level attention layer sets up the comment rq_{xy} made by learner x for course y consisting of the words $\{m_1, m_2, \cdots, m_n\}$. Among these words, only a few keywords may determine the sentence meaning expression. Therefore, this layer generates weights of word-sentence meaning relationships based on the word attention mechanism and outputs the attention representation vector $e_{rq_{xy}}$ of rq_{xy}, as shown in.

$$e_{rq_{xy}} = \sum_{n\varepsilon_{rq_{py}}} a_{ny} e_{m_n}, \tag{5}$$

where $\alpha_{\mathbf{ny}}$ denotes the attention weight of $\mathbf{e}_{\mathbf{m_n}}$, $\mathbf{e}_{\mathbf{m_n}}$ denotes the embedding vector of words m_n, and rq_{xy} denotes the total number of words in the comment. To accurately train the word influence weights, a two-layer feedforward neural network is used to parameterize the word-level attention function f_1, which is then normalized to a probability distribution using a softmax function. As shown in (6) and (7).

$$f_1\left(\mathbf{e}_{\mathbf{m_n}}, \mathbf{v_y}\right) = \mathbf{m}_1\left(tanh\left(\mathbf{M}_3\left(v_y \odot \mathbf{e}_{\mathbf{m_n}}\right) + \mathbf{h}_3\right)\right) + \mathbf{h}_4, \tag{6}$$

$$\boldsymbol{\alpha}_{\mathbf{ny}} = \text{softmax}\left(f_1\left(\mathbf{e}_{\mathbf{m_n}}, \mathbf{v_y}\right)\right), \tag{7}$$

where M_3 and $\mathbf{m}_1$ are the weight matrix and weight vector, respectively; $\mathbf{h}_3$ and $\mathbf{h}_4$ are the bias terms in the corresponding layers; $\mathbf{v_y}$ is the course vector in the interaction sequence; and $\odot$ represents the element-wise product.

The information of learners' comments under different courses at the sentence-level attention layer contains rich preference features. After the extraction of preference weights at the word level, the attention mechanism is applied again to analyze the key features in different comments to obtain the overall feature representation $\varphi_{\mathbf{p}}$ of learners' historical comments, as shown in formulas (8)–(10).

$$f_2\left(\mathbf{u_x}, \mathbf{e}_{\mathbf{rq_x}}\right) = \mathbf{m}_2\left(tanh\left(\mathbf{M}_4\left(\mathbf{u_x} \odot \mathbf{e}_{\mathbf{rq_{xy}}}\right) + \mathbf{h}_5\right)\right) + \mathbf{h}_6, \tag{8}$$

$$a_{\mathrm{xy}} = \text{softmax}\left(f_2\left(u_{\mathbf{x}}, e_{\mathbf{rq_{xy}}}\right)\right), \tag{9}$$

$$\boldsymbol{\varphi}_{\mathbf{p}} = \sum_{x=1}^{|rq_x|} \alpha_{\mathbf{xy}} e_{\mathbf{rq_x}}, \tag{10}$$

where $\mathbf{M}_4$ and $\mathbf{m}_2$ are the weight matrix and weight vector, respectively; $\mathbf{h}_5$ and $\mathbf{h}_6$ are the bias terms in the corresponding layers; $\mathbf{u}_\mathbf{x}$ represents the feature vector of the target course; f_2 is the sentence-level attention function; $\alpha_{\mathbf{xy}}$ is the sentence-level attention weight; and $|rq_x|$ is the total number of evaluated courses for learner x.

The interaction features θ_p and comment features φ_p of the learner are spliced into a new matrix $P^f = [\theta_p, \varphi_p]$ and continue to input it into the two-layer fully connected network to capture the nonlinear relationships in the data, and finally obtain the hidden vector P of the learner.

2.3.2. Feature Extraction of Course Multiple Attributes. Course attributes can be divided into structured and unstructured attributes, and feature extraction is performed in different ways according to the attribute types. The structured attributes such as course category and course duration are stitched together and embedded directly to obtain the feature matrix Q^s. Course attributes can be divided into structured and unstructured attributes, and feature extraction is performed in different ways according to the attribute types. For the unstructured textual information (course description), text-CNN is used to analyze the content in depth and forms a more differentiated abstract feature representation. The specific process is as follows.

First, the description text is divided into words, and the words are converted into a word vector matrix.

Next, the word embedding matrix is fed into the convolution layer.

Then, the network training parameters are simplified by downsampling for feature map dimensionality reduction in the pooling layer. Here, the maximum pooling operation is chosen for the compression of the feature map.

Finally, the extracted features are integrated after a fully connected layer. A fixed size text feature vector Q^{ts} is output using the Relu activation function.

The obtained Q^s and Q^{ts} are spliced into a new feature matrix. The attention mechanism is used to analyze the contribution weight of different attributes to accurately represent the course features.

2.3.3. Association Clustering Analysis of Course Categories. Course category is an important attribute of a course, due to the associative relationship between different categories of courses. And there may also be some commonalities among the interaction sequences of different learners. Therefore, to increase the recommendation coverage, the original course category labels and learner interaction sequences are combined, and the courses are further classified using the improved FP-growth algorithm and the affinity propagation algorithm, and the newly generated category labels are used as models inputs. The affinity propagation (AP) algorithm is a graph-based clustering method that automatically determines the number of clusters and forms high-quality cluster centers through message passing between data points.

To improve the mining efficiency of the FP-growth algorithm, improvements are made in the direction of reducing the number of scans of the transaction database and optimizing the structure of the FP-tree. First, the item header table is abandoned and a two-dimensional matrix is used to store the information of the item set. Since the item header table needs to scan the database once to generate it, the number of times to traverse the database is reduced once. Second, the FP-tree construction is extended and a new tree structure MGFP-tree (matrix and group frequent pattern-tree) is proposed. Since the association relationship between frequent items in the original transaction is not fully utilized in the process of generating the FP-tree, the efficiency of frequent pattern mining is reduced. In the newly constructed MGFP-tree, the group nodes stored in the array can be used to quickly construct the frequent pattern tree and discover the set of frequent items in the original transaction.

The transaction database D is scanned and mapped into a matrix $\boldsymbol{D_{wit}}$. The first column in $\boldsymbol{D_{wit}}$ represents the different items X_x $(x \leq W)$ in a transaction. Each row indicates the value corresponding to each item X_x in each transaction T_y $(y \leq T)$. The value is marked as 1 if it exists, otherwise it is marked as 0. An auxiliary one-dimensional array count is set to record the number of each item X_x. The rows that do not satisfy the minimum support threshold are also deleted according to the values stored in the array count. Finally, to facilitate the subsequent MGFP-tree generation, the rows are sorted in descending order according to the different support degrees corresponding to each item in count.

The relationship of each group has been established by grouping, similar to a tree hierarchy stored in an array. First, the values are taken from the array according to the size of the end values in the group. If the value is valid, it is assigned to the wrapped Itemset Tree object and the auxiliary root node root is created. Finally, the nodes are inserted into the binary tree sequentially through the post-order traversal of the binary tree and the parenttrace and parent properties. Figure 5 presents the MGFP-tree storing the grouped nodes. *end* means the subscript position of the end of each group, which is convenient for the quick establishment of the tree. *parent* means the father node of different groups in the same column, if there is none, it is empty. *parenttrace* property means the path information of each group, if the name and *parenttrace* of group1 and group2 are the same, the count of group1 will be added to 1. And the count of group2 will be set to 0, and valid will be set to 0. If the *name* and *parenttrace* of group1 and group2 are the same, the count of the group1 will be added to 1. The count of the group2 will be set to 0, and the *valid* will be set to 0, which can further reduce the memory space and time for building frequent pattern trees.

The number of children count of each node is counted by subsequent iterations and the count value is assigned to *tempcount*, which is used to store the new node count. Since the leaf node has no children, the relationship between the left child and the parent node can be obtained quickly. If the *nodename* of the left child node contains the *nodename* of

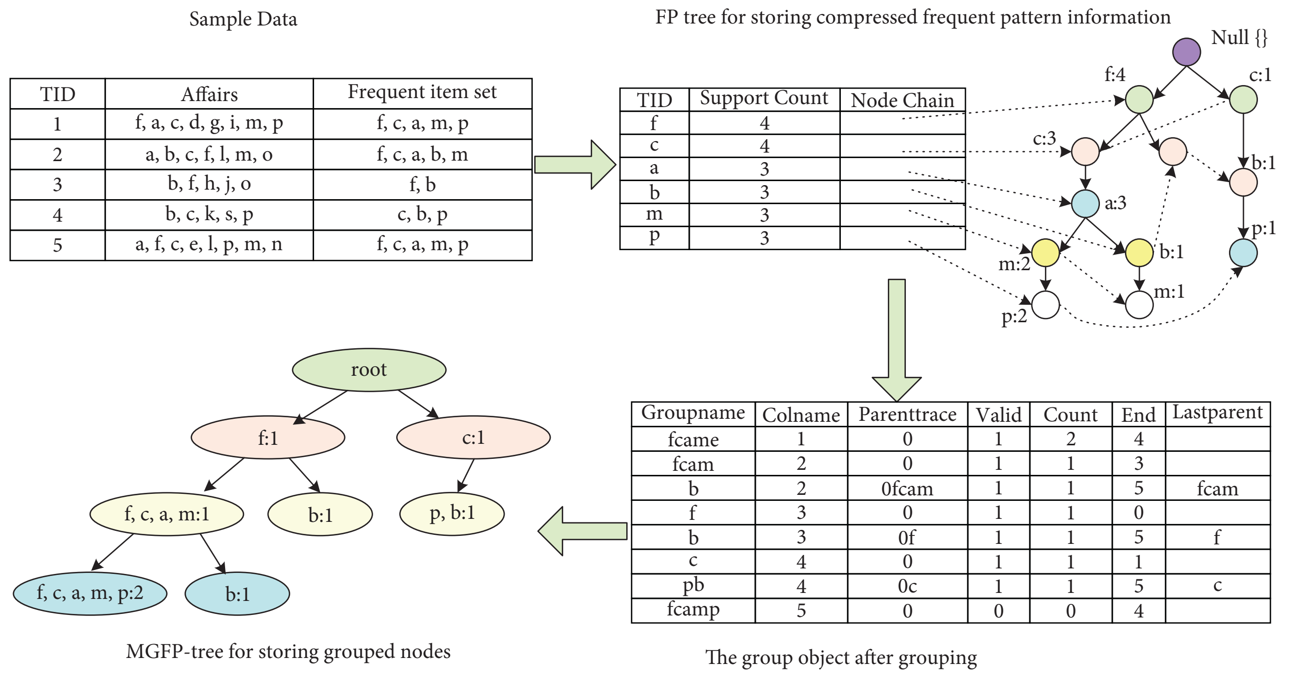

Figure 5: MGFP-tree with grouped nodes stored.

the parent node, the *tempcount* of the parent node is updated to the *tempcount* of the left child node plus the tempcount of the father node. Add the items in the right subtree that are different from the parent node to the *nodesplit* of the parent node and use it to compare with the *nodesplit* of the left subtree comparison. If the traversal process contains the same items, the *nodesplitcount* value of the *nodesplit* is added by 1. Finally, the *nodesplitcount* value of each node is compared with the minimum support, and if it is satisfied, it is combined with the parent node to produce a frequent *itemset*.

The AP algorithm needs to calculate the similarity between data points as input, so first the frequent 2-item set in the learner-course interaction set is mined using the improved FP-growth algorithm to populate the similarity matrix with its support. Since the actual interaction set is sparse, all the course IDs in it are transformed into initial category IDs and then subjected to association clustering analysis. The course category generation algorithm for associative clustering analysis is shown in Figure 6.

3. Experimental Data Analysis

3.1. Parameter Setting. The optimal parameters were determined using the grid tuning method. The parameters in Coursera and iCourse data sets are set as follows: batch size = 128 (256), learning rate = 0.001 (0.005), dropout ratio = 0.2 (0.5), and hidden units = 50 (100). Text-CNN sets four convolution kernels of $2*64$, $3*64$, $4*64$, $5*64$ ($2*128$, $3*128$, $4*128$, $5*128$). Number of convolution kernels = 100, convolution step = 2, embedding dimension dim = 64 (128), and *min*_sup = 0.7 (0.4), $\eta = 0.3$ (0.5).

When building the deep neural network model, the data are divided into training and testing sets in the ratio of 8 : 2. Supervised training is performed using a fivefold cross-validation approach, and the Adam optimization algorithm is used to update the weight parameters of the neurons in the model and adjust the training error until the model is optimal.

3.2. Performance Comparison of Improved FP-Growth Algorithm. Two sets of experiments were conducted to calculate the algorithm running time by changing the minimum support threshold, and the experimental pairs are shown in Figure 7.

From the experimental results in Figure 7, it can be seen that the running time of both algorithms decreases as the minimum support increases, but MG-FP-growth is more efficient. The mushroom data set is relatively dense, and there is a huge set of frequent items. While improved FP-growth algorithm groups the frequent itemsets in each set of transactions and reduces the branching of the tree. It can discover frequent patterns faster, so it runs faster. T10I4D100K data set is relatively sparse and has a large difference in length between each transaction, indicating that its frequent itemsets are small relative to the item nodes, so they are basically the same. However, MG-FP-tree uses a matrix to store transaction information and only needs to scan the transaction database once, so it works a little better.

3.3. Performance Comparison of Recommendation Algorithms. The experiment was evaluated using three metrics: Hit Radio (HR), Normalize Discount Cumulative Gain (NDCG), and Coverage. HR is often used to measure recommendation recall. NDCG is a measure of ranking accuracy, where the more relevant the recommendations are, the higher the NDCG and the better the

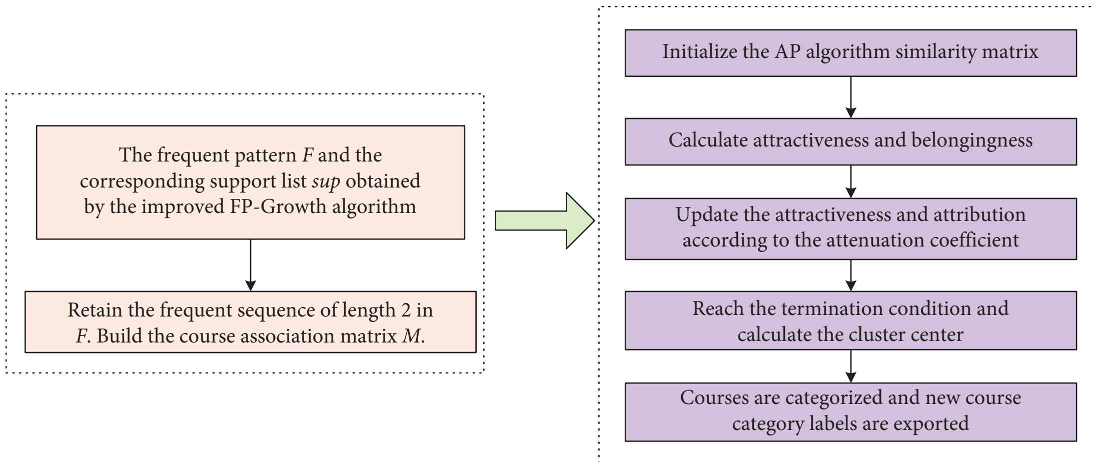

Figure 6: Course category generation algorithm for associative clustering analysis.

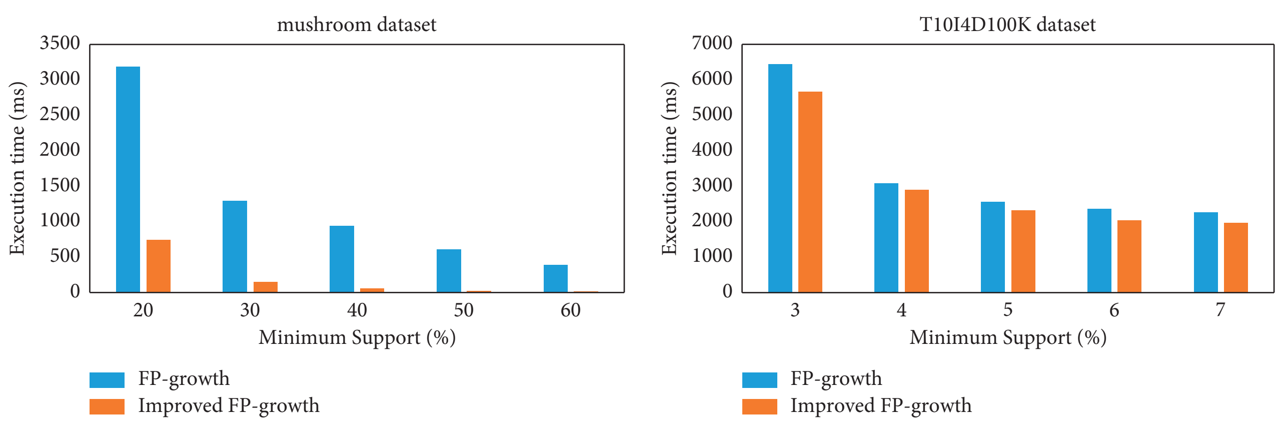

Figure 7: Running time on different dataset.

recommendations are. Coverage defines the ability of recommendation results to discover the long tail of items. The information entropy is used to calculate the coverage COV, and the larger the information entropy, the smaller the long-tail effect of the system and the higher the recommendation coverage.

To evaluate the performance, the proposed recommendation model is compared with the following five related recommendation methods: A course recommendation method combining learner fit and course matching degree in literature [25]. A recommendation method based on implicit trust perception in the literature [26]. A recommendation method based on deep Bayesian ranking in literature [27]. A recommendation method based on graph neural network in literature [28]. Improved FC-LFM recommendation method in the literature [29]. The performance comparisons on the iCourse dataset are list out in Figures 8–10.

For specific analysis, literature [25] calculates course fit and pairing based on item similarity and the FP-growth algorithm. The accuracy of the algorithm is low because it only calculates course similarity based on learners' course selection records and the pairing combination of two courses is sparse. Literature [26] mines implicit trust relationships

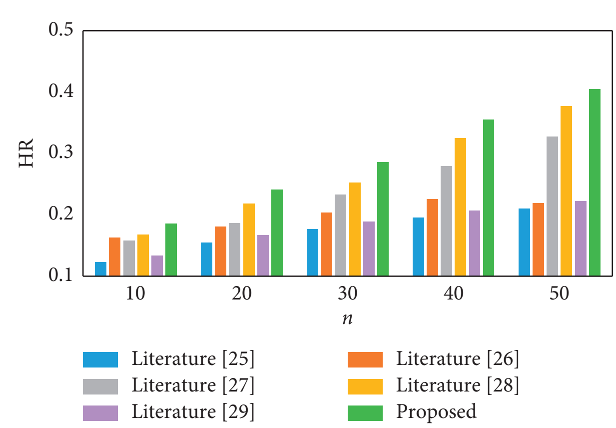

Figure 8: HR performance comparison on iCourse data set.

based on learning input degree, which improves the performance compared with literature [25]. However, it is found in the experiments that the learners' engagement is mainly concentrated in the same smaller interval. The use of Pearson's correlation coefficient tends to lead to overlap when calculating similar relationships. The performance

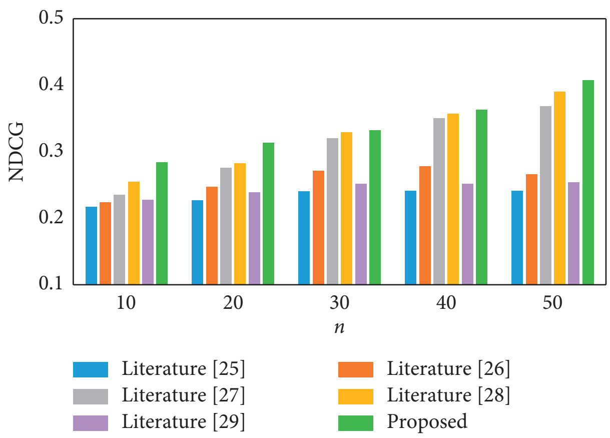

Figure 9: NDCG performance comparison on iCourse data set.

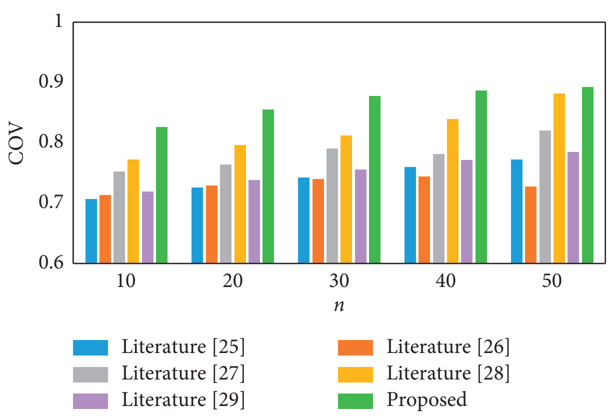

Figure 10: COV performance comparison on iCourse data set.

growth slows down or even decreases when n exceeds 30. Literature [27] uses Bayesian ranking to mine the differences in learners' pairwise course preference. The input uses a neural network to encode the features of historical course records and course IDs, and each learner's learning records are sampled only once. The NDCG improvement is very obvious when $n \leq 30$, but the improvement is smaller on COV. The literature [28] utilizes learner-course and course-category interaction dichotomous graphs to model learning relationships and course relationships. The recommendation performance rises more significantly with increasing n using aggregation functions to capture higher order implicit relationships between nodes based on BPR optimized preference prediction. The literature [29] adopts automatic clustering based on user behavior based on the data itself, which leads to low accuracy due to data sparsity issues. The proposed model incorporates more factors to enrich the feature extraction process of learners and courses and refines key features in multivariate information through an attention mechanism. The best performance on the three metrics and the more stable growth rate indicate that the method in this paper has strong applicability for course recommendation.

The running times of all methods on both data sets are given in Table 1. Further analysis shows that literatures

Table 1: Comparison of running times of different methods.

Method	Running time (s)	
	Coursera	iCourse
Literature [25]	6.15	9.01
Literature [26]	11.57	14.66
Literature [27]	851.82	911.04
Literature [28]	1425.52	2093.78
Literature [29]	11.57	14.66
Proposed	1194.46	1241.6

[25, 26] and [29] are the traditional collaborative filtering recommended methods with the shortest running time but lower accuracy. The running time of the proposed model in this paper is between literatures [27, 28]. Since the complexity of literature [28] depends mainly on the number of nodes in the interaction graph, the running time increases significantly on iCourse where the number of learners and courses is much higher. And the proposed model complexity is related to the length of the input feature sequences, mainly the sequence length of the unstructured attributes of the features (comments, interaction sequences, and course description text). These features vary relatively little on different data sets, so the training time cost is within a manageable range. The performance of the proposed model is optimal among all methods, thus facilitating the recommendation of more appropriate and effective courses and resources.

4. Conclusion

Online course construction model design and application is an important way to promote English teaching reform in the education information environment, and a new education model that responds to the individual development demands of student groups. The online course model takes a student-centered teaching model and builds a new relationship between teaching and learning. For the selection of English online course resources, this paper makes full use of the rich contextual features of online networks and proposes a multifeature fusion recommendation model. The model is designed with a multilevel attention mechanism to model key information in learner interaction sequences, review texts, and multiple attributes of courses, representing features' learners and course feature accurately. The association clustering analysis is also introduced to increase the coupling degree among courses. Finally, probability matrix decomposition is applied to optimize the recommendation model and generate predicted scores. The experiments indicate that the recommended performance of the proposed model is better than the existing methods. The shortcoming of this paper is that objective factors such as learner interest migration and intercourse dependencies are not considered. More in-depth research will be conducted in this area in the future.

Data Availability

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

Conflicts of Interest

The author declares no competing interests.

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