# A Personalized Recommendation Method for English Online Teaching Video Resources Based on Machine Learning

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**Abstract.** In order to optimize the utilization of learning resources, provide learners with English online teaching video resources that meet their learning needs and interests, and achieve intelligent recommendation of English online teaching video resources, a machine learning based personalized recommendation method for English online teaching video resources is proposed to address the problem of poor accuracy in personalized recommendation of traditional methods for English online teaching video resources. Using clustering algorithms to classify English online teaching video resources and extract the features of English online teaching video resources. Using graph convolutional neural networks in deep learning to predict users' preference for English online teaching video resources, obtain recommendation results, and achieve personalized recommendation of English online teaching video resources based on deep learning. The experimental results show that the method has a recommendation accuracy of 92% for 300 users, a video resource recommendation recall rate of 91%, a recommendation path completion rate of 95%, and a recommendation time of 5 s, resulting in better recommendation performance.

**Keywords:** Machine Learning · Online English Teaching · Teaching Videos · Personalized Recommendation of Resources

## 1 Introduction

With the rapid development of internet technology, in the field of English learning, as more and more people begin to accept the new mode of online education, English online education has become the first choice for many people to learn English. On online learning platforms, the massive amount of English teaching video resources provides students with rich learning content and resources. However, how to select suitable content for students from the massive video resources has become an important issue faced by the education industry. Traditional online English education platforms mostly rely on manual or conventional recommendation algorithms to classify videos. Students need to spend a lot of time and energy to find the content they are interested in or suitable for, and they


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are likely to miss other high-quality learning resources [1]. At the same time, traditional recommendation algorithms fail to fully consider students' learning needs and interests, and the recommended content often fails to meet students' expectations. Therefore, in order to solve the above problems, more and more researchers are exploring the use of personalized recommendation technology to improve the user experience and learning effectiveness of online English education platforms. By analyzing users' learning history and behavior, personalized recommendation systems can provide customized teaching video resources for each user, better meeting their learning needs and improving English learning effectiveness [2].

Reference [3] proposes a personalized English resource recommendation method based on knowledge graphs. By analyzing some problems that arise in traditional classroom teaching and online English teaching, various knowledge points in English teaching are classified and corresponding knowledge graphs are formed. Secondly, annotate relevant knowledge points in online teaching. Then, the daily learning behavior of students was analyzed to obtain a characteristic graph of their learning behavior. Finally, collaborative filtering technology and content-based recommendation technology are combined to provide more English teaching resources for learners to better meet their personal needs. Reference [4] proposes a massive online learning resource recommendation method based on multi-objective optimization. Model the learning resource recommendation task as a multi-objective optimization problem. Based on multi-objective evolutionary algorithm, the massive online learning resource recommendation is achieved through four steps: recommendation, clustering, optimization goal setting, individual representation, and calculation of genetic operators. Reference [5] proposes an immersive contextual teaching method for college English based on machine learning in artificial intelligence and virtual reality technology. Through a comparative teaching experiment on two classes of freshmen in a certain university, the experimental class conducted immersive virtual situational teaching based on VR technology from a constructivist perspective, while the control class used common multimedia devices and traditional teaching methods. The experimental results indicate that the combination of constructivist theory and virtual reality technology in immersive contextual teaching of college English can indeed improve students' English proficiency. The above methods have certain effectiveness, but the accuracy of personalized recommendation for English online teaching video resources still needs to be improved.

In recent years, with the continuous maturity of artificial intelligence technologies such as deep learning and machine learning, personalized recommendation algorithms have also been continuously innovated and optimized. Based on this, this article proposes a personalized recommendation method for English online teaching video resources based on machine learning, aiming to provide English learners with a more personalized, efficient, and comprehensive learning experience. This method combines the clustering algorithm and graph Convolutional neural network in deep learning, and combines the two to achieve the classification and feature extraction of English online teaching video resources, and predicts users' preferences for resources based on the deep learning model. Deep learning models can better capture users' interests and behavior patterns, thereby achieving more accurate personalized recommendations. By integrating different technical methods together, more comprehensive and accurate recommendation results are provided.

## 2 Preprocessing of English Online Teaching Video Resources Based on Machine Learning

This article uses clustering algorithms to classify English online teaching video resources, which can classify similar video resources into one category and extract the features of English online teaching video resources, better reflecting the content and characteristics of video resources. The graph Convolutional neural network in deep learning is introduced to predict users' preferences for English online teaching video resources. By modeling the relationship between users and resources, the graph convolution neural network can better capture users' interests and behavior patterns, so as to achieve more accurate and personalized recommendations. This method can effectively extract common features between video resources and provide a foundation for subsequent recommendation processes.

### 2.1 Analysis of the Categories of English Online Teaching Video Resources

The clustering algorithm is used to analyze the collected English online teaching video resources and divide different objects into different clusters. Because the clustering algorithm belongs to unsupervised learning, the classification analysis is completed under the premise of unknown target conditions. The most famous clustering algorithm is the K-Means algorithm. The K in the K-Means algorithm represents the number of sample classifications, and the specific values depend on the actual situation. The implementation process of the algorithm is as follows:

Assuming that given the training sample $\left\{x^{(1)}, x^{(2)}, \cdots, x^{(n)}\right\}$ of English online teaching video resources, each $x^{(i)} \in R^n$, does not include label information $y$.

Randomly select $K$ cluster centroid point and represent it as $u_1, u_2, \cdots, u_n \in R^n$.

Loop through the following steps until convergence:

Calculate the class to which each video resource sample $i$ belongs:

$$c^{(i)} = \arg\min_j \left\| x^{(i)} - u_j \right\|^2 \tag{1}$$

Calculate the similarity between each sample and the centroid point [6], and use Euclidean distance as the evaluation criterion for similarity. Select centroid points with a small distance from the sample, and divide the samples with the same centroid distance into the same cluster to complete the initial classification of the samples.

Recalculate the centroid points for each cluster $j$:

$$u_j = \frac{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\} x^{(i)}}{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\}} \tag{2}$$

For video resource sample data of the same category, recalculate the centroid points of that category to complete the data update. This article uses the average value of sample data from the same category [7–9] as the basis for updating centroids. Repeat the above operation until convergence occurs.

### 2.2 Extracting Features of English Online Teaching Video Resources

In order to improve the processing speed of matching user search terms with English online teaching video resources, the features of English online teaching video resources are extracted and output in the form of feature vectors. The word frequency feature refers to the number of times a given word appears in English online teaching video resources, and its expression is:

$$TF_c = \frac{T_c}{T} \tag{3}$$

Among them, $T$ and $T_c$ are the total number of words in the English online teaching video resources and the number of times words $c$ appear in the English online teaching video resources, respectively. Due to the large amount of data in English online teaching video resources, there may be extraction bias in the process of word frequency feature extraction. Therefore, the concept of inverse document word frequency is introduced [10–12]. In the process of extracting inverse document word frequency features, it is believed that the higher the frequency of a word appearing in an English online teaching video resource, the lower the frequency of that word appearing in all resources, Indicates the thematic prominence of the word in the designated English online teaching video resources [13–15]. In addition to keywords, the authority and citation of English online teaching video resources can also reflect the characteristics of the resources to a certain extent, and their feature vector expression is:

$$\begin{cases} Authority = \frac{1}{2}Level + \frac{1}{2}Cite \\ Cite = \frac{Cites}{\max Cite} \end{cases} \tag{4}$$

Among them, *Level* and *Cite* are the quantitative results of the publication level and citation volume of English online teaching video resources, respectively, while *Cites* and max *Cite* correspond to the citation volume of the resources and the largest citation volume in the resource source database [16]. Use the same method to extract and fuse feature vectors, and ultimately obtain the comprehensive feature extraction results of English online teaching video resources [17].

### 2.3 Calculate the Similarity Between User Interests and English Online Teaching Video Resources

In the process of calculating the similarity between user interests and English teaching video resources, the keywords searched by learners are used as user interest features to obtain the similarity between user interests and English online teaching video resources. The formula for calculating the shortest path between search keywords and user interests in English online teaching video resources is as follows:

$$\text{ShortestPath}(\gamma_2, \gamma_1) = \begin{cases} \text{ShortestPath}\ (\gamma_2, \gamma_1) \\ 1 \quad (\textit{if}\ \ \gamma_2 \in \lambda\phi_i \text{ and } \gamma_1 \in \lambda\phi_i) \\ 0 \quad (\textit{if}\ \ \gamma_2 = \gamma_1 \text{ or } \gamma_2 \text{ and } \gamma_1 \text{ no path exists}) \end{cases} \tag{5}$$

According to the collaborative filtering principle, the definition formula of the interest correlation degree between user interest point $\gamma_2$ and interest point $\gamma_1$ is:

$$KCD(\gamma_2, \gamma_1) = \begin{cases} \frac{in|\gamma_2|}{\text{ShortestPath}(\gamma_2, \gamma_1)} \\ 0 \quad (\textit{if} \ \text{ShortestPath} \ (\gamma_2, \gamma_1) = 0) \end{cases} \tag{6}$$

From the above equation, it can be seen that when the shortest distance between user interest points $\gamma_2$ to $\gamma_1$ is not equal to zero, the interest correlation degree between user interest points $\gamma_2$ to $\gamma_1$ is the shortest distance ShortestPath$(\gamma_2, \gamma_1)$ between interest points $\gamma_2$ to $\gamma_1$. When the shortest distance between interest points $\gamma_2$ to $\gamma_1$ is zero, it indicates that there are no identical interest points for English online teaching video resources between user interest points $\gamma_2$ to $\gamma_1$. When there is no relationship between interest points, it can be considered that the interest point has no value to the user and its similarity can be set to 0.

In the collaborative filtering English online teaching video resource database $\Omega(\vartheta, \chi)$, $\vartheta$ represents the combination of user interest points, and $\chi$ represents the set of similarity between user interest points. For user $\xi$ with historical search behavior, their point of interest $\lambda(\xi)$ is a collection of interest points for all English online teaching video resources that the user has searched for historically. The English online teaching video resource database $\lambda(\xi)$ includes a combination of interest points for all English video teaching $\varsigma$. The connection between Resource $\varsigma$ and the English online teaching video resource database represents the resource connection between User Interest $\varsigma$ and English online teaching video resource $\xi$. The calculation formula is as follows:

$$KCD(\varsigma, \xi) = \sum_{\varepsilon_i \in \lambda(\varsigma)} \frac{in|\varepsilon_i|}{\text{ShortestPath} \ (\varepsilon_i, \lambda(\xi))} \tag{7}$$

Among them, $\varepsilon_i$ represents any user interest point in the English online teaching video resource database, the depth of the user interest point $|\varepsilon_i|$ represents the importance of the user interest point, and ShortestPath $(\varepsilon_i, \lambda(\xi))$ represents the shortest path of all user interest points [18–20].

After calculating the connectivity between user interest points and English online teaching video resources, the similarity between user interest points and English online teaching video resources is calculated using the connectivity of English online teaching video resources. The calculation formula is as follows:

$$\text{Interest}(\xi, \varpi) = \frac{1}{|\Re(\xi)|} * \sum_{j \in \Re(\xi)} \frac{\overrightarrow{\omega_i} \cdot \overrightarrow{\omega_j}}{|\overrightarrow{\omega_i}| \cdot |\overrightarrow{\omega_j}|} \tag{8}$$

Among them, $\xi$ represents the set of user interest points, $\varpi$ represents the set of keywords that users search for in English online teaching video resources, $\Re(\xi)$ represents the set of user historical interest points, $|\Re(\xi)|$ represents the number of historical English teaching video resources, and $\overrightarrow{\omega_i}$ and $\overrightarrow{\omega_j}$ represent the similarity between English online teaching video resources $i$ and $j$, respectively. In the calculation process of similarity, the higher the similarity between user interests and English online teaching video resources, the closer the preferences of English online teaching video resources and user interest points are, indicating that the English online teaching video resources are more worthy of recommendation.

## 3 Personalized Recommendation of English Online Teaching Video Resources Based on Deep Learning

Using graph convolutional neural networks in deep learning to predict users' preference for English online teaching video resources. A heterogeneous graph constructed using $P = \langle W, U \rangle$ representation, where set $W$ represents all nodes, nodes in $W$ are divided into two categories: $X$ and $Y$, $X$ represents the set of English online teaching video resource nodes $x$, and $Y$ represents the set of user nodes $y$; Set $U$ represents all edges, and the edges in set $U$ are also divided into two categories. The interaction behavior $a_{xy}$ generated by user $y$ and English online teaching video $x$ constitutes one type of edge set $A$, and the switching behavior generated by user $b_{ij}$ from English online teaching video $i$ to English online teaching video $j$ constitutes another type of edge set $B$. The weight of this edge $\theta$ is determined by the number of times the user switches in the dataset. If $\theta = 0$, no switching behavior occurs, that is, the edge does not exist.

Design an embedding layer based on unique hot coding based on user identity identification. Construct an embedding layer matrix $C$ for $m$ user and an embedding layer matrix $E$ for $n$ English online teaching video resources. If the dimension of $C$ is $m \times D$, the dimension of $E$ is $n \times E$, where $D$ represents an adjustable low dimensional spatial dimension. Set unique hot coding $\phi_y$ and $\phi_x$ for the user and English online teaching video resources respectively, and combine matrices $C$ and $E$, The low dimensional representation vectors $c_y$ and $e_x$ for users and English online teaching video resources can be obtained as follows:

$$\begin{cases} c_y = C^T \phi_y \\ e_x = E^T \phi_x \end{cases} \tag{9}$$

In the personalized recommendation algorithm for English online teaching video resources, users' preferences need to be divided into two parts: long-term preferences and short-term preferences, and modeled separately. Among them, long-term preferences are fixed preferences that users do not easily change over time, and vice versa, short-term preferences.

Modeling the user's long-term preferences through the representation vector of all English online teaching video resources nodes that the user has watched. This involves propagating and aggregating all English online teaching video resources that the user has watched to the user nodes. $B_y$ represents the set of all English online teaching video resources that the user $y$ has interacted with, and $Y_x$ represents the set of all users who have watched English online teaching video resources $x$, $\alpha_l^{(k+1)}$ and $\beta_l^{(k+1)}$ respectively represent the network parameters and offset parameters when propagating from layer 1 to layer $k+1$, $\vartheta$ represents the nonlinear activation function, $aggregate(\cdot)$ represents the vector aggregation operation, $g_{y-l}^{(k)}$ and $g_{y-l}^{(k+1)}$ represent the user $y$ layer $k$ and layer $k+1$ representation vectors, $h_{x-l}^{(k)}$ and $h_{x-l}^{(k+1)}$ represent the video $x$ layer $k$ and layer

$k + 1$ representation vectors, and the propagation formulas of $g_{y-l}^{(k+1)}$ and $h_{x-l}^{(k+1)}$ are as follows:

$$\begin{cases} g_{y-l}^{(k+1)} = \vartheta\left(\alpha_l^{(k+1)}\left(g_{y-l}^{(k)} + aggregate\left(h_{x-l}^{(k)}|x \in Y_x\right)\right) \right.\\ \qquad\qquad \left. +\beta_l^{(k+1)}\right) \\ h_{x-l}^{(k+1)} = \vartheta\left(\alpha_l^{(k+1)}\left(h_{y-l}^{(k)} + aggregate\left(g_{x-l}^{(k)}\middle|y \in B_y\right)\right) \right.\\ \qquad\qquad \left. +\beta_l^{(k+1)}\right) \end{cases} \quad (10)$$

Modeling the short-term preferences of users through the representation vector of their previous interaction behavior, that is, the directed edge from the previous English online teaching video resource to the next English online teaching video resource serves as the propagation path of the vector. This can decouple the modeling of long-term preferences and short-term preferences, avoiding mutual influence between the two.

Use set $R_x$ to represent all videos with $x$ directed edges, $\alpha_s^{(k+1)}$ and $\beta_s^{(k+1)}$ to represent network parameters and bias parameters when propagating from layer 1 to layer $k + 1$, $aggregate(\cdot)$ represents vector aggregation operation combined with weights, $h_{x-s}^{(k)}$ and $h_{x-s}^{(k+1)}$ represent video $x$'s $k$ and $k + 1$ layer representation vectors, $h_{i-s}^{(k)}$ represents the next English online teaching video resource $i$'s $k$ layer representation vector, and the propagation formula for $h_{x-s}^{(k+1)}$ is as follows:

$$h_{x-l}^{(k+1)}=\vartheta\left(\alpha_s^{(k+1)}\left(h_{y-s}^{(k)} + aggregate\left(h_{i-s}^{(k)}|i \in R_x\right)\right) +\beta_s^{(k+1)}\right) \quad (11)$$

Based on the long and short term preference vector propagation, two components of English online teaching video resources were obtained, and the two components were merged to obtain a user preference comprehensive vector $h^{(k+1)}$ as follows:

$$h^{(k+1)} = h_{x-l}^{(k+1)} + h_{x-s}^{(k+1)} \quad (12)$$

After obtaining user preferences, calculate the cosine similarity between user preference feature vector $h^{(k+1)}$ and target English online teaching video resource cosine similarity $\omega$ of feature vector $\eta_{s_i}$:

$$\omega=\frac{\sum_{k=0,i=1}^{N}\left(h^{(k+1)} \times \eta_{s_i}\right)}{\sqrt{\sum_{k=0}^{N}\left(h^{(k+1)}\right)^2}\sqrt{\sum_{i=1}^{N}\left(\eta_{s_i}\right)^2}} \quad (13)$$

Among them, $N$ is the vector dimension.

Combining user preferences for English online teaching video resources with $\omega$ calculating user preferences for target English online teaching video resources, $f_{pq}$ setting the similarity between English online teaching video resources $i$ and $j$ as $\omega_{ij}$, user $y$ preference for $v$ types of English online teaching video resources as $T(y, v)$, and user $y$

preference for good English online teaching video resources as $B_y$, The set of $L$ English online teaching video resources with the highest similarity to English online teaching video resources $i$ is $K(i, L)$, and the recommended result $f_{pq}$ is as follows:

$$f_{pq} = \underset{j \in v}{T}(y, v) \sum_{i \in B_y} \omega_{ij} \tag{14}$$

Obtain the top $f_{pq}$ user preference based on actual needs, generate a recommendation list, and complete personalized recommendation of English online teaching video resources based on deep learning.

In summary, the flowchart of the personalized recommendation method for English online teaching video resources based on machine learning is shown in Fig. 1.

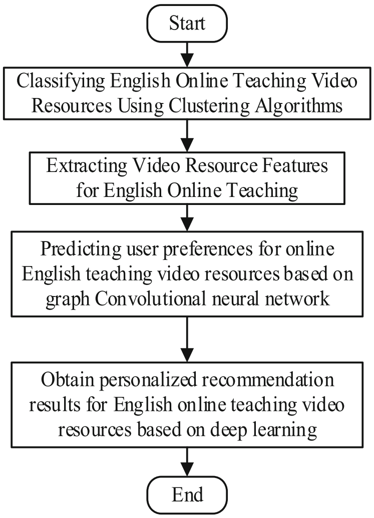


**Fig. 1.** Flow chart of personalized suggestion method for online teaching video resources based on machine learning

# 4 Experimental Analysis

## 4.1 Experimental Preparation

In order to test the performance of the personalized recommendation method for English online teaching video resources based on machine learning, 300 users were selected for testing, and their data sources covered multiple majors in a certain university. Among them, students majoring in computer science, Electronic engineering and information technology accounted for 30% of the total, students majoring in business management, marketing and international trade accounted for 30% of the total, students majoring in education, psychology and sociology accounted for 20% of the total, and students majoring in other fields of literature, art, medicine and engineering accounted for 20% of the total. The data sources of these 300 users can include multiple channels such as user registration information, user behavior data, user interest surveys, user reviews and feedback, and social media data. By comprehensively analyzing these data, we can better understand users' needs and interests, and provide data support for the testing and optimization of personalized recommendation methods based on machine learning.

And the following testing environments were deployed:

Hardware environment: a processor with a frequency of 2.4 GHz and two computers with a Windows 7 operating system;

Software environment: 32-bit server, Windows 7 operating system, and MySQL database.

The specific testing process is as follows: users first browse all English video teaching resources according to the operating steps, select the teaching video resources they are interested in, and record the recommended results based on the learning process.

### 4.2 Setting Evaluation Indicators

In order to verify the recommendation effectiveness of the recommendation system in the article, accuracy, recall, and recommendation path completion are selected as evaluation indicators, and the calculation formula is:

$$A = \frac{TP + TN}{TP + FP + FN + TN} \tag{15}$$

$$D = \frac{TP}{TP + FN} \tag{16}$$

Among them, $A$ represents accuracy, $D$ represents recall, $TP$ represents the amount of correctly recommended teaching video resources, $TN$ represents the amount of correctly recommended other data, $FP$ represents the amount of incorrectly recommended teaching video resources, and $FN$ represents the amount of unrecommended teaching video resources.

The higher the accuracy and recall rate of the system, the better the accuracy and effectiveness of the system in the application process. The higher the completion of the recommended path, the higher the success rate of teaching video resource recommendation, and the better the recommendation effect can be achieved.

### 4.3 Analysis of Test Results

In order to highlight the effectiveness of the recommendation system in the article, the methods of reference [3] and reference [4] were compared to test the accuracy, recall, and recommendation path completion of three methods in recommending English video teaching resources. The results are as follows.

The accuracy test results of English video teaching resource recommendation using three methods are shown in Fig. 2.

The results of Fig. 2 show that the accuracy of recommending English video teaching resources using the methods of reference [3] and reference [4] is below 80%, while the

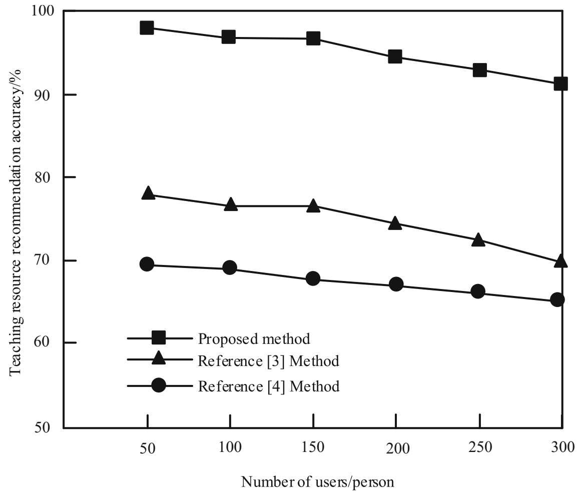


**Fig. 2.** Test results of accuracy in recommending English online teaching video resources

accuracy of recommending English video teaching resources using the proposed method is 92% for 300 users. This indicates that the proposed method can accurately classify English online teaching video resources using machine learning algorithms and extract English online teaching video resources that users are interested in, Effectively improving the accuracy of recommendations.

The recall rate test results of English video teaching resource recommendations using three methods are shown in Fig. 3.

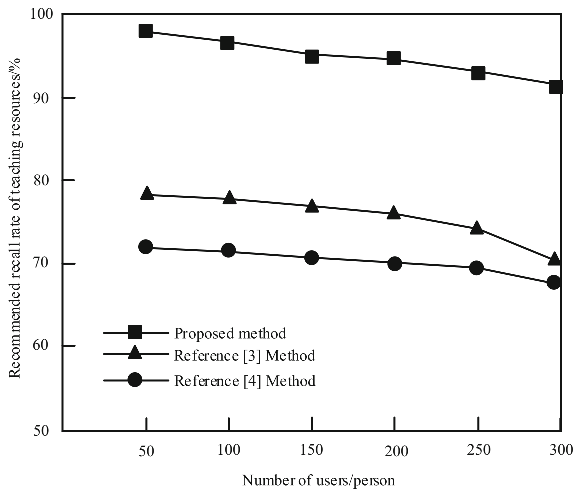


**Fig. 3.** Results of the recall rate test for English online teaching video resources recommendation

From the results in Fig. 3, it can be seen that in the recall test, the video resource recommendation recall rates of the methods in reference [3] and [4] are both below 80%, while the video resource recommendation recall rate of the proposed method is 91%, indicating that the recommendation effect of the proposed method is better.

The recommended path completion test results of the three methods are shown in Fig. 4.

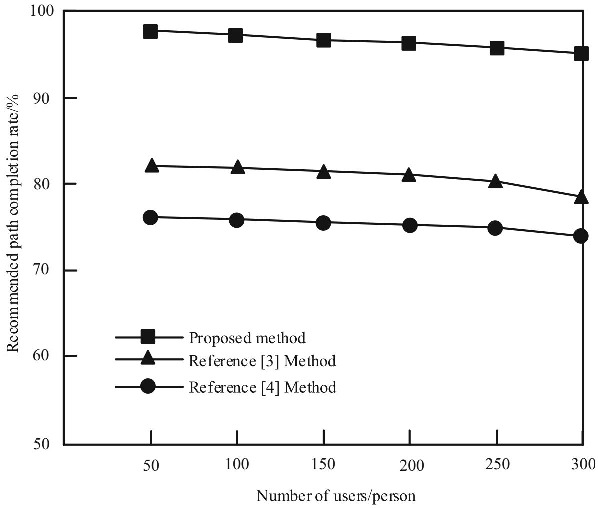


**Fig. 4.** Completion Test Results of Recommended Path for English Online Teaching Video Resources

According to the results in Fig. 4, it can be seen that the recommended path completion test results of the methods in reference [3] and reference [4] are relatively close, both between 70% and 85%. However, when using the proposed method to recommend English video teaching resources, the recommended path completion rate for 300 users is 95%, which can accelerate the success rate of English video teaching resources recommendation and have better recommendation effects.

On this basis, the time consumption of personalized recommendation of English online teaching video resources using three methods was tested, and the experimental comparison results are shown in Fig. 5.

Analyzing Fig. 5, it can be seen that the recommended English online teaching video resources for the method in reference [3] take 20 s, the recommended English online teaching video resources for the method in reference [4] take 14 s, and the recommended English online teaching video resources for the method in this article take 5 s. The English online teaching video resource recommendation method proposed in this article takes less time and the efficiency of the recommendation algorithm is good.

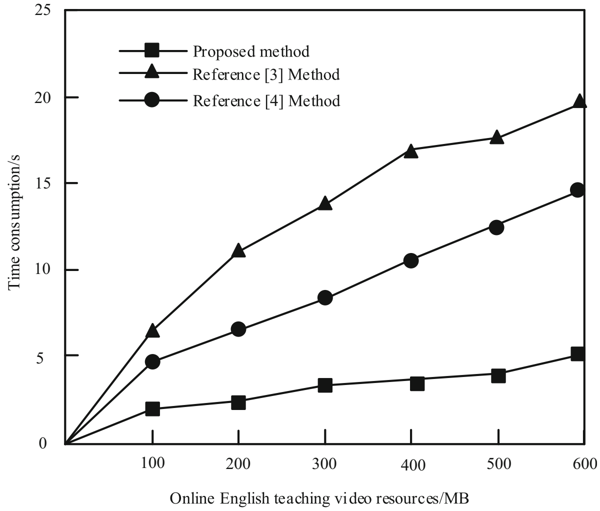


**Fig. 5.** The time-consuming test results of recommending English online teaching video resources

# 5 Conclusion

This study proposes a personalized recommendation method for English online teaching video resources based on machine learning technology. By preprocessing and analyzing multidimensional data such as students' learning behavior, a personalized recommendation model is constructed to achieve personalized recommendation of English online teaching video resources. Compared with traditional English online teaching video resource methods, this method has better recommendation accuracy, recall rate, and recommendation path completion.

In addition, this study explores the application of machine learning technology in the recommendation of English online teaching video resources by optimizing and validating the model, providing new ideas and methods for related research. In the future, we will continue to improve this method, improve recommendation accuracy and coverage, and strive to achieve greater practical results in students' English learning and online English education.

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