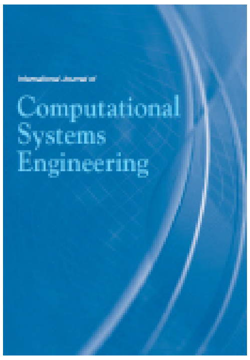

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A study of personalised recommendation methods for multimedia ELT online course

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Abstract: Aiming at the problem that a large number of online courses lead to the reduction of students' efficiency in finding suitable courses, the collaborative filtering recommendation algorithm is improved. The 'user project' scoring matrix is used to calculate the reasonable scoring factors. At the same time, the 'user project' scoring matrix and project characteristics are used to establish a composite feature matrix. Then, combined with demographic information, a mixed user model is established to obtain a neighbourhood set close to the real situation, and finally the best recommendation result is generated. The improved hybrid user model collaborative filtering algorithm (IHUMCF) is used for personalised recommendation. Compare IHUMCF with HUMCF and UBCF. The results showed that IHUMCF recommended the most in the same time; IHUMCF has the highest accuracy rate, recall rate and comprehensive evaluation index, and the lowest average error. It shows that collaborative filtering recommendation algorithm based on improved hybrid user model can improve the accuracy of personalised recommendation, provide better recommendation effect, and analyse students' potential learning needs to provide students with a better online learning environment.

Keywords: collaborative filtering algorithm; multimedia English teaching; online courses; personalised recommendation.

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1 Introduction

Multimedia is one of the most powerful teaching aids in the modern world and is becoming more and more frequent in English language teaching. As a kind of multimedia teaching, online courses enrich the learning environment for students, allowing them to watch online courses several times in order to review and consolidate their knowledge, further enhancing their learning efficiency. It also increases the degree of college students' interest in English, and improving their active learning of English, thus promoting their commitment to English as a whole and improving their overall level of proficiency, and facilitating the development of English teaching. At the same time, the popularity of online courses allows teaching classes and teaching resources to be recycled, greatly saving teachers' working time and improving their efficiency (Fu et al., 2019). However, due to the wide variety of online courses, selecting the right online course will take a lot of time and effort, resulting in a lower level of interest in the student body in choosing English online courses, which is not conducive to the growth and development of English language teaching in the long run. The use of collaborative filtering algorithms to personalise recommendations for students' multimedia English language teaching online courses can save students' time in finding suitable online courses and provide students with suitable online courses while being able to obtain students' potential learning needs from their learning behaviour. Therefore, the recommendation algorithm can not only meet students' current online course learning needs, but also solve the problem of recommending students' future online learning courses, forming a complete and continuous recommendation list, which can in a certain way improve students' subjective motivation for English learning and enhance their overall English language proficiency and ability. However, the algorithm cannot carry a large number of users, and when the number of users in the system keeps increasing, the workload of the user similarity matrix within the recommendation algorithm increases substantially, making it take longer to generate recommendation results as well as reducing the effectiveness of the recommendations (Xu et al., 2019). The collaborative filtering recommendation algorithm based on the improved hybrid user model solves this problem and has been widely used, and the algorithm has been verified to have higher accuracy. In view of this, the algorithm was improved, i.e., a collaborative filtering recommendation algorithm using an improved hybrid user model, in order to improve the accuracy of the recommendation results and recommend more appropriate online courses for students to facilitate their English learning and English language teaching. The improved algorithm adds user information and online course categories to the user item ratings and then combine them with the hybrid user model built from the 'user-item' matrix to make the recommendation results more realistic and reasonable while being rich in information (Yin et al., 2019). The addition of a reasonable user rating factor to the similarity calculation can improve the differences in user scales and make the predicted ratings more realistic and reliable, thus making the recommendations generated by the collaborative filtering algorithm based on the improved hybrid user model better, recommending more suitable online courses for students, improving students' learning efficiency and promoting the development of English multimedia English teaching.

2 Related work

The collaborative filtering algorithm is one of the most utilised algorithms in recommendation systems, and the personalised recommendations generated using this algorithm have been well received and have solved many recommendation needs. Therefore, it is widely used in many fields. Many scholars have combined collaborative filtering with recommendation algorithms to produce personalised recommendations, and many research results have been achieved.

In order to solve the problems such as sparse matrix scoring of collaborative filtering algorithm, Aljunid and Manjaiah (2020) improved the collaborative filtering algorithm using matrix decomposition technique to obtain a deep learning method based on collaborative recommendation system, and the research results indicated that the improved algorithm has higher recommendation accuracy than the original algorithm and the algorithm takes less time to produce recommendation results. Salunke et al. (2020) used collaborative filtering algorithm to predict users' song style preferences based on their listening history and provided users with suitable recommendation results for their listening list on a daily basis, in response to the difficulty of selecting users' favourite songs from a huge song library. Liu and Zhang (2021) proposed a personalised recommendation algorithm based on knowledge graphs to address some shortcomings of the current knowledge graph recommendation algorithm, and the results showed that the hit rate and average reverse ranking were improved using this algorithm. Ding et al. (2019) designed an optimised recommendation algorithm to address the problem of fewer personalised recommendation results for ethnic handicrafts. Combining the use of two recommendation algorithms, and then realising the recommendation of Miao batik products, the results showed that the improved algorithm reduced the recommendation error, improved the recommendation accuracy, and promoted the development of the Miao batik industry. Ji (2019) proposed an improved collaborative filtering algorithm in order to make cross-border e-commerce inventory and sales more balanced, and the improved algorithm to a recommendation system, and the results showed that the imbalance in inventory and sales could be solved using the improved algorithm, which promoted the development of cross-border e-commerce.

Li et al. (2021) used a collaborative filtering algorithm for personalised recommendation in order to improve the speed of users in finding books of interest in libraries, and the similarity between books and books was calculated, and the results showed that the algorithm could provide users with effective personalised book recommendations and save the speed of users in finding books of interest. Yang et al. (2021) solve the problem of poor recommendation effect of collaborative filtering algorithm, the collaborative filtering algorithm was improved by using the user's historical behaviour data to calculate the similarity of the user; the improved slope one algorithm and nearest neighbour set were used to predict the rating of items and obtain the recommendation results; the results showed that the improved algorithm produced better recommendation effect and wider application. Built a recommendation model for a retail pharmacy marketing system and a recommendation model for a retail pharmacy in order to improve the recommendation effect of pharmaceutical marketing system; the experimental results showed that these two models can recommend suitable drugs for users as well as find target users for drugs, which is beneficial to the marketing of pharmacies (Lv and Kong, 2021).

The above is a discussion of the personalised recommendations of collaborative filtering algorithms by scholars from different fields. It can be seen that the optimised collaborative filtering algorithm produces good recommendations. Given the wide variety of online courses in multimedia English teaching and the time spent by students in finding suitable online courses, this paper will use the improved collaborative filtering algorithm to improve the recommendation effect of online courses, saving time and effort for users while providing a better environment for English online learning.

3 ELT online course recommendation result construction

3.1 *Improved collaborative filtering algorithm*

Collaborative filtering (CF) recommendation algorithms are used in a wide range of applications, combining nearest neighbour techniques to analyse and calculate relevant historical data of the target object to achieve personalised recommendations for the target user (Li and Li, 2019). Among them, collaborative filtering recommendation algorithms are divided into two categories based on different contents, which are memory-based and model-based (Tao et al., 2019). Among them, the memory-based classification algorithm contains two sub-categories of users and items. The item-based algorithms recommend based on similar items, and their recommendation fundamentals are shown in Figure 1.

Figure 1 Basic principle of algorithm (see online version for colours)

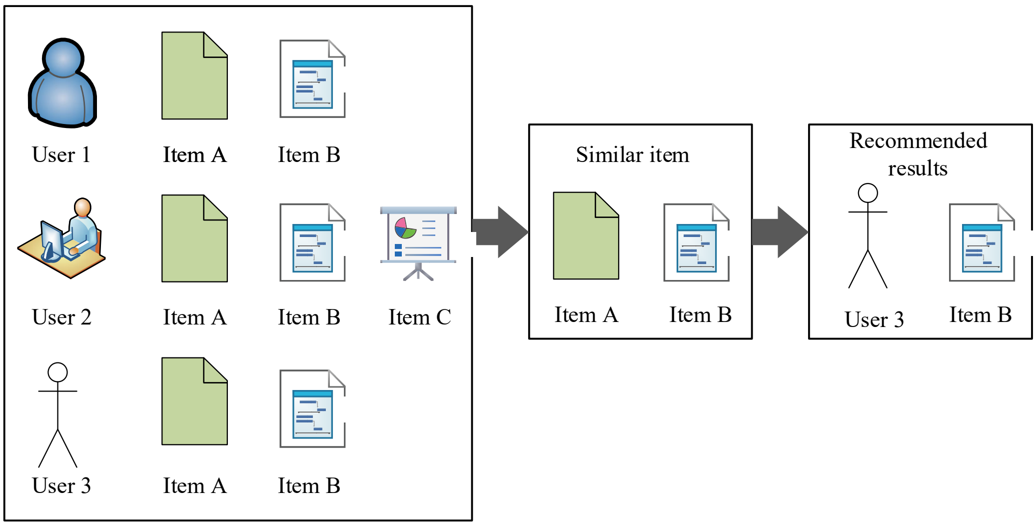
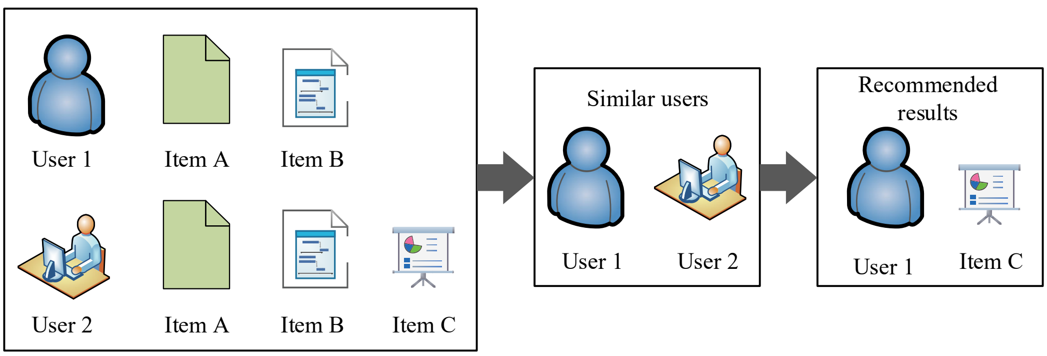


Figure 2 Basic principle of UserCF (see online version for colours)



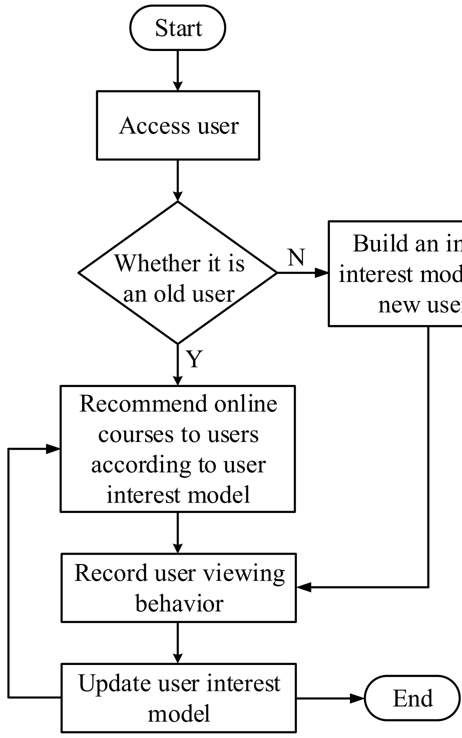
As can be seen from Figure 1, the collaborative filtering recommendation algorithm based on items first calculates the similarity based on the information about the item. When the target object is interested in an item, the recommendation result can be obtained by relying on the similarity between the objects and the content that they usually like. If a user is interested in item A and also likes item B, this means that the two items have a high degree of similarity; when the third user is interested in item A, it can be inferred that user 3 is more likely to be interested in item B. Since ItemCF only needs to analyse the user's own historical choices and not the historical behavioural data of other users, the recommended results are more reliable. The algorithm is less computationally intensive than UserCF, and the computation process is less complicated than UserCF, so users can get the recommended results faster (Chaabi et al., 2020). However, some studies have shown that this algorithm does not produce final recommendation results calculated with high accuracy and does not provide users with very appropriate recommendation results. This drawback is overcome by UserCF, which is based on user-item rating data and assumes that users with similar interests have a high probability of liking similar things, and has become the most used and successful algorithm in personalised recommendation. The basic principles are shown in Figure 2.

In Figure 2, UserCF first uses a rating matrix I to describe the user's evaluation data of the item, then uses statistical methods to obtain a neighbour formation with similar interests to the target user, then relies on the recent interests of the nearest-neighbour set to predict the rating value of the item to be recommended. The nearest-neighbour set is then used to predict and recommend items to be recommended. The accuracy of the recommendations generated by UserCF is high when there is a large amount of data in the recommendation system and the information is complete. However, when the number of users in the system keeps increasing, the delay in computation time makes the system significantly less efficient. To address these issues, a collaborative filtering recommendation algorithm (IHUMCF) with an improved hybrid user model is proposed. IHUMCF combines demographic information in the collaborative filtering algorithm, as the user model of IHUMCF contains the content of interest and some personal information of the target audience, thus improving the recommendation effect. The IHUMCF firstly calculates the scoring reasonableness factor based on the 'user-item' scoring matrix, and then uses the 'user-item' scoring matrix and item features to build a combined feature matrix, and then combines the demographic information to build a mixed user model. In addition, IHUMCF proposes a new similarity calculation method, which can solve the scale difference problem of user ratings. IHUMCF introduces a reasonable factor of user ratings in the user similarity calculation process, which can improve the user similarity calculation method and improve the accuracy of finding the nearest neighbour set.

3.2 Design of a personalised recommendation model for English online courses based on collaborative filtering algorithms

The use of collaborative filtering recommendation algorithms to personalise recommendations for students' multimedia EFL online courses requires predictive scoring of users in terms of their needs for online courses based on a combination of user interest models, and recommending predictive scoring values to users in descending order (Chen et al., 2020). Therefore, a user interest model needs to be built first, as shown in the flowchart in Figure 3.

Figure 3 Flow chart of user interest model



The model can accurately reflect the user's real interests and learning needs, and is a key part of the recommendation system. Then, on the basis of the user interest model, personalised online courses can be recommended to the user, and the specific recommendation process is shown in Figure 4.

Figure 4 Flow chart of online course recommendation

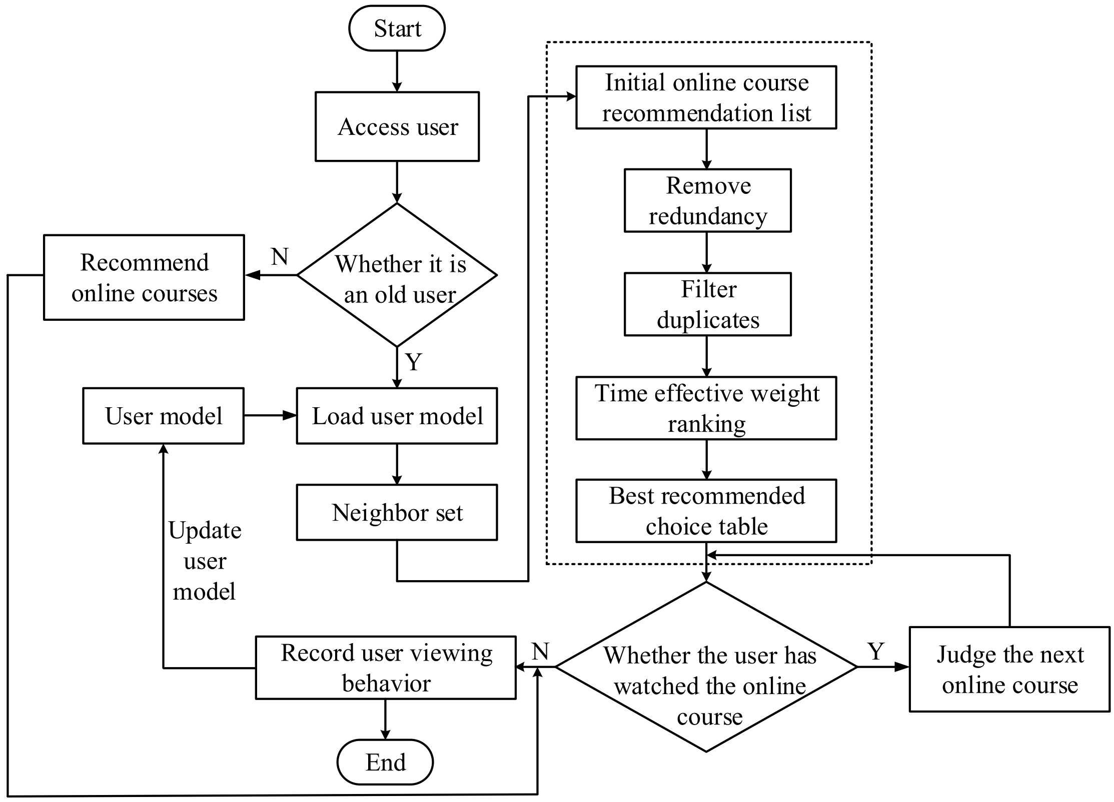


Table 1 User rating data

Online courses	*Users*					*Categories*				
	U1	*U2*	*U3*	*U4*	*U5*	*C1*	*C2*	*C3*	*C4*	*C5*
W1	5	3	0	4	3	1	1	0	0	1
W2	5	0	3	0	5	0	1	1	1	0
W3	4	0	2	1	3	0	1	0	1	0
W4	5	2	0	2	5	1	0	0	0	1
W5	5	3	2	0	5	1	0	1	0	1
W6	0	5	2	4	1	0	1	1	1	0
W7	2	4	0	1	3	1	0	0	1	1
W8	0	5	2	3	0	1	0	1	0	0
W9	3	1	0	5	1	0	1	0	0	1
W10	2	0	4	1	3	1	0	1	1	1

Table 2 Category rating list

Users	$\lvert T_i \rvert$	*TI*	*C1*	*C2*	*C3*	*C4*	*C5*
U1	8	31	5, 5, 5, 2, 2	5, 5, 4, 3	5, 5, 2	5, 4, 2, 2	5, 5, 5, 2, 3, 2
U2	7	23	3, 2, 3, 4, 5	3, 5, 1	3, 5, 5	5, 4	3, 2, 3, 4, 1
U3	6	15	2, 2, 4	3, 2, 2	3, 2, 2, 2, 4	3, 2, 2, 4	2, 4
U4	8	21	4, 2, 1, 3, 1	4, 1, 4, 5	4, 3, 1	1, 4, 1, 1	4, 2, 1, 5, 1
U5	9	29	3, 5, 3, 3, 3	3, 5, 3, 1, 1	5, 5, 1, 3	5, 3, 1, 3, 3	3, 5, 5, 3, 1, 3

As can be seen from Figure 4, this recommendation process can be completed by identifying more similar behaviours in the dataset after statistical sorting of the relevant information collected from users to recommend the course content preferred by the subject to be recommended. Statistical analysis of the viewing behaviour and ratings of some users of the online course is shown in Table 1.

Table 1 counts the ratings of 5 users for 10 online courses, of which 10 online courses include 5 categories such as career, examination, level 4 and 6, and speech, all of which are important courses for university students to learn English. W_k denotes the online course, $k \in [1, 10]$; U_i represents the user, $i \in [1, 5]$; U_i is the rating of the user's preference for the online course, the score range is generally [1, 5], the higher the user's preference for the course, the higher the rating; if the user does not rate, the score is 0; C_j is the category of the online course, $j \in [1, 5]$, denotes workplace English, exam English, grade 4 English, grade 6 English and speech English, respectively, W_k belongs to the category C_j, then the corresponding category score is 1, otherwise it is 0. Table 1 can also be seen as the user's rating matrix I, $I = \{I_{ik}\}$, I_{ik} to describe the user's i rating of the item, $kT_i = \{k \mid I_{ik} \geq 1\}$ in the sense of the user's rating value for the level of interest in all online courses, $|T_i|$ to describe the sum of the number of items rated by the i^{th} user, including valid and invalid ratings, this rating will be filtered out and eliminated and only valid ratings will be accepted, $TE_i = \left\{k \middle| I_{ik} \geq \frac{m}{2}\right\}$ to describe the set of valid ratings. $|TE_i|$ is the number of items rated by the user i, and $TE_i \subseteq T_i$; m is the maximum of the estimated ratings, and a rating greater than or equal to $\frac{m}{2}$ is a valid rating, if the rating is less than $\frac{m}{2}$ then it is screened out. $TI(i)$ denotes the sum of ratings of all items evaluated by the user i, $TI(i) = \sum_{k \in T_i} I_{ik}$; $CI(i, j) = \sum_{j \in C_j \subseteq T_i} I_{ij}$ represents the sum of valid ratings of the user i for the online course category j and satisfies $I_{ij} \geq \frac{m}{2}$, where C_j denotes the set of online courses satisfying the category; $j|C_j|$ denotes the attribute frequency, i.e., the number of valid ratings of the user i for the items matching the category j (Tian et al., 2019). This results in a table of user ratings for each category of the online course, as shown in Table 2.

The rating values of different users for different online course categories can be seen in Table 2, and the level of interest of users in different online course categories can be seen in Table 2. The category interest CIM of the user i for the category j is shown in equation (1).

$$CIM(i, j) = \frac{\dfrac{CI(i, j)}{TI(i)} \times \dfrac{\sum_{j \in C_{j \subseteq TH_i}} p_r}{|T_i|}}{\dfrac{CI(i, j)}{TI(i)} + \dfrac{\sum_{j \in C_{j \subseteq TH_i}} p_r}{|T_i|}} \tag{1}$$

In equation (1), $CI(i, j)$ indicates the interest level of users i in the category j; $p_r = \left(I_{ij} - \frac{m}{2} + 1\right) \Big/ \left(\frac{m}{2} + 1\right)$, p_r are the weights of the online course category j and the rating value I_{ij} determines the weight value (Chen et al., 2019). The results obtained using equation (1) can more accurately reflect the level of interest of users in the online courses. The distribution of ratings obtained by three users rating the online courses numbered 1–1,000 is shown in Figure 5.

Figure 5 Distribution of scores (see online version for colours)

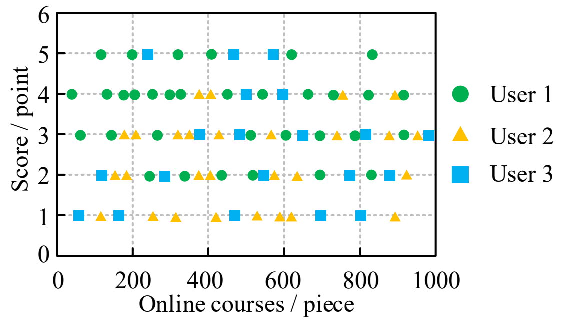


Figure 5 shows that the rating values for user 1 are distributed in the interval [2, 5] , the rating values for user 2 are distributed in the interval [1, 4] and the rating values for user 3 are distributed in the interval [1, 5]. The online course with a rating of 3 for user 1 is a medium course, while the course with the same rating of 3 is a better course for user 2. It can be seen that the differences in user ratings will affect the calculation of similarity rates between users, which will further affect the accuracy of the final recommendation results. To address this issue, the accuracy of personalised recommendations for online courses can be improved by using the user's reasonable rating factor ω_i, which is calculated as follows

$$\omega_i = \sqrt{\frac{\sum_{j \in T_i} \left(I_{ij} - I_i'\right)^2}{|T_i|}} \tag{2}$$

In equation (2), I is the rating matrix, I_{ij} is used to describe the rating of the online course category by the ji user, $|T_i|$ is used to describe the total number of ratings by the i user, and $T_i = \{j \mid I_{ij} \geq 1\}$, I_i' is used to describe the mean rating of the i user, $I_i' = \frac{TI(i)}{|T_i|}$; ω_i is used to describe the reasonableness of the rating of the i user. The larger the value of ω_i indicates that the difference between the ratings of each item by the i user is greater, indicating that the difference between the items preferred by the users is greater, but the effect on the similarity is not significant. The effect on similarity is not significant. In order to obtain the optimised similarity, a combination of rating reasonableness factors was calculated as shown in equation (3).

$$sim'(i_1, i_2) = \frac{\sum_{k=1}^{n} \left| (S_{i_1k} - S'_{i_1}) \times (S_{i_2k} - S''_{i_2}) \right| + \sum_{k=n+1}^{n+q} \left| w_{i_1}(S_{i_1k} - S'_{i_1}) \times w_{i_2}(S_{i_2k} - S'_{i_2}) \right|}{\sqrt{\sum_{k=1}^{n} (S_{i_1k} - S'_{i_1})^2 \times (S_{i_2k} - S'_{i_2})^2} \times \sqrt{\sum_{k=n+1}^{n+q} \left[w_{i_1}(S_{i_1k} - S'_{i_1})^2 \right] \times \left[w_{i_2}(S_{i_2k} - S'_{i_2})^2 \right]}} \tag{3}$$

In equation (3), S_{i_1k} is used to describe the rating of the online course by the i_1 user, S_{i_2k} is used to describe the rating of the online course by the i_2 user, S'_{i_1} is used to describe the average of all rating items of the i_1 user, S'_{i_2} is used to describe the average of all rating items of the i_2 user, w_{i_1} is used to describe the rating reasonableness factor of the i_1 user, w_{i_2} is used to describe the rating reasonableness factor of the i_2 user, the meaning of $sim'(i_1, i_2)$ is the similarity between the users i_1 and i_2, the greater the similarity between the two users, the greater the value obtained. The greater the similarity between two users, the greater the calculated value; the calculated results are sorted in descending order, and the top N users with the greatest similarity are selected as the nearest neighbour set of the target user (Ma et al., 2021). The calculated nearest neighbour set was also used to predict ratings for items that had not yet been rated by the target user, with the formula shown in equation (4).

$$D(i, j) = S'_{i_1} + \frac{\sum_{k \in U} sim'(i_1, i_2) \times (S_{ki_2} - S'_{i_2})}{\sum_{k \in U} sim'(i_1, i_2)} \tag{4}$$

In equation (4), $D(i, j)$ represents the predicted rating of the item by the user ki, S'_{i_1} is used to describe the average of all items already rated by the i_1 user, S'_{i_2} is used to describe the average of items already rated by the i_2 user, and U represents the set of nearest neighbours. By calculating the similarity, the predicted rating value can be obtained and the top N items with the highest total rating can be calculated and recommended to the target user as the best recommendation list (Yan and Xie, 2020).

4 Experimental design and results analysis of personalised recommendations for multimedia ELT online courses

4.1 *Construction of a personalised recommendation system for multimedia ELT online courses*

The personalised English web course recommendation system is designed to use user logs as the raw data for experiments to analyse the behavioural characteristics of users for the purpose of customising personalised web courses for them. When a user searches for an online course and watches it, the recommendation system records the behaviour generated by the user in the current online course, specifically including the user's watch time, watch history, and search dwell time. The recommendation system also takes into account the accuracy, efficiency, potential learning needs and updates of the recommendations to ensure that the online courses in its generated recommendations meet the users' learning needs and can explore the users' future learning needs through their learning behaviour, and the user model can be updated automatically. The development and operating environment of the recommendation system is shown in Table 3.

Table 3 Development and operation environment

Number	*Equipment and environment*	*Correlation coefficient*	*Tool*	*Unit*
#1	Operating system	Windows 7	/	/
#2	Memory	8	/	GB
#3	CPU	Intel (R) Core (TM) CPU T7200, 2.50 HZ	/	/
#4	Development language	/	Python	/
#5	Development tool	/	FLASH, Director, MySQL	/

The recommended system developed was a Windows 7 computer system with good performance to work with the recommended system; and with 8 GB of memory to store a lot of data. Python was utilised as the development language and FLASH, Director and MySQL were used as development tools.

4.2 *Analysis of the results of personalised recommendations for multimedia ELT online courses*

A comparison of the time and number of recommended results generated by IHUMCF, UBCF and HUMCF yields Figure 6.

Figure 6 Comparison diagram of three algorithms (see online version for colours)

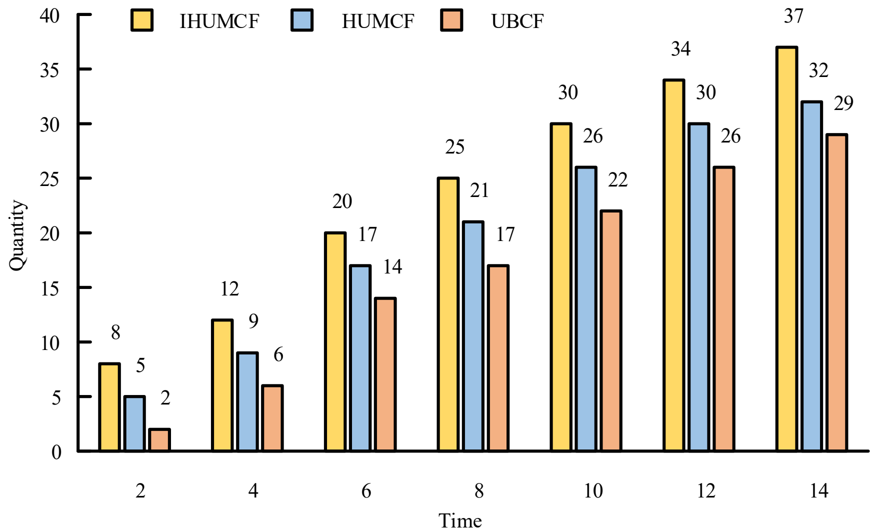


Figure 7 Growth rate of recommended quantity of three algorithms (see online version for colours)

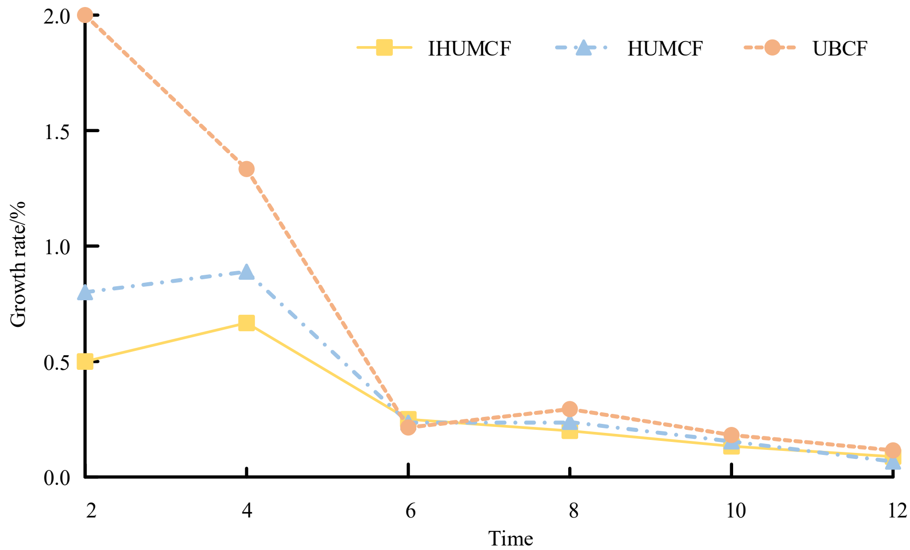


Figure 8 Satisfaction of different users with the recommendation results generated by the three algorithms (see online version for colours)

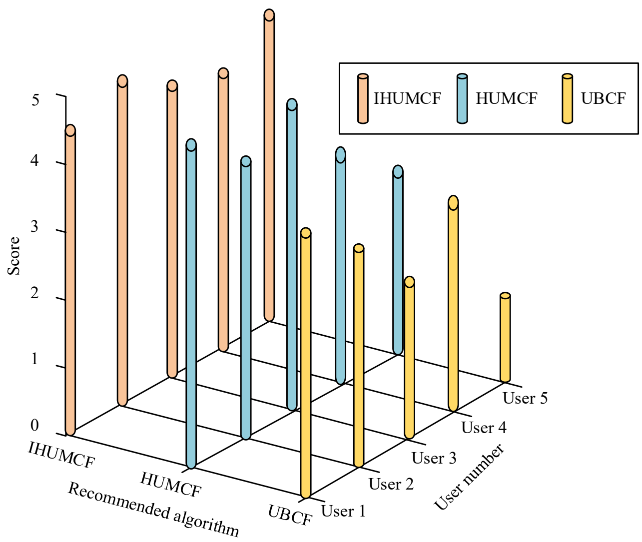
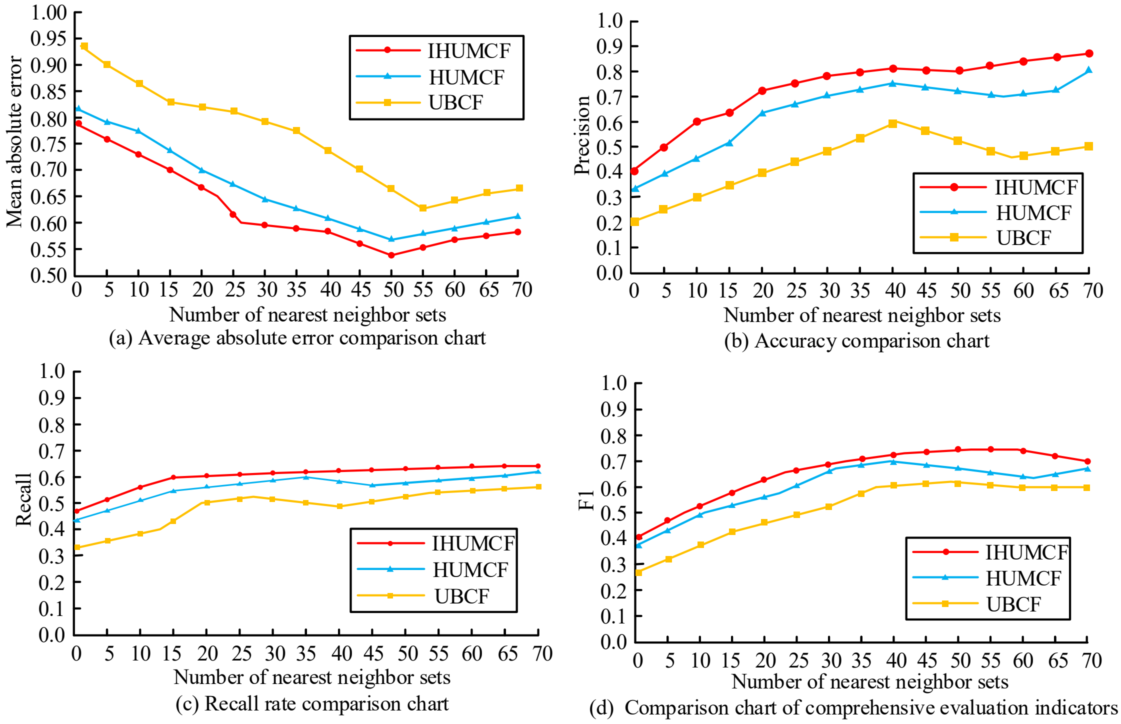


Figure 9 Comparison diagram of three algorithms (see online version for colours)



(a) Average absolute error comparison chart
(b) Accuracy comparison chart
(c) Recall rate comparison chart
(d) Comparison chart of comprehensive evaluation indicators

In Figure 6, the horizontal coordinates are time in seconds and the vertical coordinates are the recommended results in units of one. From the figure, it can be seen that the number of recommended results generated by the three algorithms gradually increases as time increases. For users, the more recommendations, the more space they can choose. IHUMCF has the highest number of recommendation results, followed by HUMCF and UBCF the least; in the simulation model, IHUMCF generates 20 recommendation results at the 6ths and 37 at the 14ths. The growth rates of the number of recommendations for each of the three algorithms are shown in Figure 7.

From Figure 7, we can see that the increase of IHUMCF, HUMCF and UBCF all decrease with the increase of time, which indicates that the recommendation algorithm needs some preparation and reflection time at the beginning of the search, and the number of recommendations of the algorithm starts to increase gradually after it is ready, so the number of recommendations of the algorithm increases more at the beginning, and the increase becomes smooth with the increase of time. IHUMCF has the smoothest increase. The results of the recommendations generated by the three recommendation algorithms were combined with five users rating them on a scale of [0, 5] and the results are shown in Figure 8.

It can be seen from Figure 8 that different users were the most satisfied with the recommended results generated by IHUMCF, HUMCF was the second most satisfied and UBCF was the lowest, indicating that users preferred the English online courses recommended by IHUMCF. A comparison of mean absolute error (MAE), accuracy, Recall and overall evaluation index F of the recommendation results obtained by IHUMCF, HUMCF and UBCF yielded a comparative graph of the three algorithms as shown in Figure 9.

In Figure 9(a), it shows the average absolute error of the three algorithms, with smaller values indicating higher accuracy of the recommendation algorithm and better recommendations. The graph shows that the collaborative filtering algorithm that improves the hybrid user model obtains the smallest average absolute error, the user-based collaborative filtering algorithm obtains the largest average absolute error, and the collaborative filtering algorithm based on the hybrid user model follows; the average absolute error of IHUMCF and HUMCF is the smallest when the number of nearest neighbour sets is in the interval [45, 55], and the accuracy of predicting ratings is the highest; the Precision[0, 1]. The average absolute error of UBCF is the smallest when the number of nearest neighbours is in the interval [50, 60], indicating that the accuracy of the predicted scores is the highest at this time. The smallest average absolute error is 0.54 for IHUMCF, 0.58 for HUMCF and 0.63 for UBCF. It indicates that the recommended item is more likely to be liked by the user. The graph shows that the accuracy of the three algorithms increases as the number of nearest neighbour sets increases, with IHUMCF having the highest accuracy, followed by HUMCF and UBCF the lowest. IHUMCF has the highest accuracy of 0.83, HUMCF has the highest accuracy of 0.80 and UBCF has the highest accuracy of 0.59.

Figure 9(c) shows the recall rates of the three algorithms. The recall rate indicates the number of items preferred by the user in the recommendation to the user versus the percentage of items preferred by the user. Recall takes the value interval [0, 1], and when the value of recall is closer to 1, it indicates that the higher the likelihood that an item preferred by a user is recommended, indicating that the algorithm is more effective in making recommendations (Gao et al., 2019). The figure shows that the recall rate is higher when the number of nearest neighbour set is higher. Among them, IHUMCF has the highest recall rate, followed by HUMCF and UBCF has the lowest. the highest recall rate is 0.65 for IHUMCF, 0.63 for HUMCF and 0.51 for UBCF. Figure 9(d) shows the comprehensive evaluation metrics of the three algorithms' F_1. In order to improve the comprehensiveness of the recommendation effect, the accuracy rate was combined with the recall rate to obtain a comprehensive evaluation metric with better recommendation effect. A higher F_1 value indicates a better recommendation effect of the recommendation algorithm. The graph shows that the number of nearest neighbour sets increases along with the value of the comprehensive evaluation metric. IHUMCF has the highest comprehensive evaluation index, followed by HUMCF and UBCF has the lowest. IHUMCF has the highest comprehensive evaluation index of 0.71, HUMCF has the highest comprehensive evaluation index of 0.69 and UBCF has the highest comprehensive evaluation index of 0.61. It can be seen that IHUMCF not only guarantees the number of recommendations, but also the quality of the recommendation results.

5 Conclusions

Due to the wide variety of online courses currently available in the English language teaching process, finding the right online course for learning can take more time and effort. In this paper, the collaborative filtering algorithm of the hybrid user model is improved to enhance the degree of personalised recommendation of online courses, and then the recommendation results obtained by IHUMCF are compared with those obtained by HUMCF and UBCF. The results show that the number of recommendation results of the three algorithms increases with time, with IHUMCF having the highest number of recommendations and significantly more than those generated by the other two algorithms; IHUMCF has the highest accuracy, recall and overall evaluation metrics, followed by HUMCF and UBCF the lowest; IHUMCF has the smallest average absolute error, followed by HUMCF and UBCF was the largest. The accuracy, recall and overall evaluation metrics of the three algorithms are also higher when there are more nearest neighbour sets. The accuracy, recall and overall evaluation indexes of IHUMCF are all above 0.65, with the highest accuracy of 0.83, the highest recall of 0.65 and the highest overall evaluation index of 0.69. This indicates that IHUMCF has the highest number of recommendation results, but also has higher accuracy and better recommendation effect, which can recommend more suitable English online courses for students, thus improving students' learning efficiency and further promote the development of multimedia English teaching. Later research will continue to further optimise the application effect of the algorithm in the recommendation function, reduce the redundant operations of users, and reduce the deviation degree of recommendations. It will also make further in-depth research and optimisation on the realisation of online video teaching functions, so that the platform can better serve users.

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