

Automatic Recommendation System of College English Teaching Videos based on Students’ Personalized Demands

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Abstract—With the emergence of computers and networks, the social needs for English competence have presented a diversified and professionalized trend. The current single teaching model can no longer satisfy students’ needs. To cater to different demands of students and improve their level of satisfaction with personalized and automatically recommended teaching videos, an automatic recommendation system of college English teaching videos, which consists of interface layer, business logic layer, and data layer, was designed. The quality of recommended teaching videos was ensured through the strict management of English teaching videos within the system. The degree of interest in videos was calculated according to students’ browsing history of teaching videos. The content of teaching videos that meet students’ personalized demands was established on the basis of the degree of interest. The Naïve Bayesian classification method was used to precisely, rapidly, and stably divide the teaching videos into two classes—interest and disinterest—according to the abovementioned information. Results show that the recall ratio and precision ratio of this system reach as high as 95.18% and 97.2%, respectively. The system recommendations averagely rank top, the recommendation precision is high, and the recommended video contents are abundant, with an applause rate of 97.79%. This designed system can establish student-centered college English teaching methods, create a favorable language environment, and better promote the teaching of English among college students.

Keywords—personalized demand, teaching video, automatic recommendation, recommendation system, video management, interest degree

1 Introduction

With the great strides made in scientific and technological development in recent years, the computer has become one of the indispensable educational tools in all colleges and universities. Online teaching has become the first choice for the self-learning of students, which aims to satisfy students’ personalized learning styles [1, 2]. In the science and technology-dominated era, mass information is mutually fused so that teaching videos are all-inclusive and more teaching videos are provided to

students [3, 4]. The mass-approach teaching videos can, to some extent, meet all learning needs of students and enrich their knowledge. However, with the dramatic rise of teaching videos and expansion of learning channels, some low-quality platforms have introduced many inferior teaching videos simply to elevate their heat degree regardless of the quality of teaching materials. Faced with wide variety resources, students can hardly find high-quality teaching videos catering to their personalized demands [5, 6].

In face of this serious social issue, many experts have studied the automatic recommendation of teaching resources. Recommendation system is a tool to guide users to find their favorite resources quickly and accurately. After processing the user’s current behavior data and historical behavior data through relevant methods, it can predict the resources of interest for users. Users can simply click on the page to obtain the information resources they want. In this way, it can greatly save users’ time cost, improve users’ experience and satisfaction, and effectively solve the problem of information overload. Cui et al. optimized the multi-classification support vector machine algorithm and used it to design an intelligent recommendation system. This system facilitated generating the association between the Rice algorithm and problem features through the selection framework of the algorithm, followed by the multi-classification transformation of problem and intelligent recommendation through the multi-classification strategy of support vector machine [7]. Liang et al. designed a video recommendation system based on video content detection. First, the spatial-temporal points of interest in the videos were extracted, a vector matrix of video sequence was constructed, the relevant vector information was acquired by using the clustering algorithm, and the grey sheep user groups were obtained through the scores, to realize the automatic video recommendation [8]. Although all of the aforementioned methods can effectively reach the goal of automatic recommendation of teaching videos, the recommended contents are too unified and monotonous, failing to meet the personalized learning needs of contemporary college students.

Due to the space and time flexibility of e-learning, e-learning has become the general trend. How to use the e-learning platform to better provide an efficient and convenient learning environment for the majority of student users has become a topic worthy of research by experts and scholars. Online learning platforms such as Netease open classes and XuetangX have launched open and free courses covering multiple disciplines and from various famous schools. In the face of such e-learning platforms and a large number of teaching video resources in Shanghai, it is imperative to provide personalized recommendation services for users with different interests. So, in this study, an automatic recommendation system of college English teaching videos based on students’ personalized demands was designed. This system was composed of interface layer, business logic layer, and data layer, which could precisely and rapidly judge and automatically recommend the related teaching videos to students with personalized demands. The proposed system combines the personalized demand information mining method and the naïve Bayesian classification method.

2 State of the art

With the high-speed development of the Internet and diversified English teaching methods, the English demand system meeting personalized needs can be built. Such system can improve the teaching methods of college English teachers and enhance their appeal, thus cultivating college students' interest in learning English and autonomous learning ability. Relevant scholars have investigated personalized college English teaching systems to different degrees. Yuan [9] established a novel teaching model named flipped English class, which highlighted the dominant position of students, promoted the digitalized, networked, and standardized development of college English teaching. However, the redundancy of English resources in the online teaching process discouraged students from precisely searching videos. In order to improve the quality of English teaching and optimize the teaching mode, Huang [10] skillfully used multimedia technology in the process of English teaching, which effectively expanded the students' knowledge and greatly stimulated the students' desire for knowledge. However, in practical application, the problems such as the mass and diversity of multimedia information were not considered. Ma [11] analyzed the personalized training direction of college students from the perspective of learners' needs. The results show that it is difficult to meet the personalized needs of College English learners at present. Therefore, the personalized needs of College English learners can be met by setting differentiated teaching objectives. Lin [12] found that with the rapid development of modern information technology, online education has become an indispensable and important part of education at all levels. English apps have been introduced into English classroom learning one after another, playing an important role in improving students' learning quality. However, the video recommendation level of mobile app needs to be further improved.

Studies on recommendation technology mostly focus on the construction of various models and the improvement of recommendation algorithms. Fan et al. [13] adopted a collaborative filtering algorithm based on multi similarity between users to make up for the lack of single score similarity. Jia et al. [14] proposed an online teaching video recommendation method based on collaborative filtering to make the recommendation more accurate. Wang et al. [15] proposed an improved algorithm for the original slope algorithm: the hybrid collaborative filtering algorithm of weighted slope one and user clustering and scoring coefficient slope one and user clustering. Experiments show that the improved accuracy is improved. To solve the problem of data scalability, Ocepik et al. [16] adopted the method of matrix decomposition to reduce the dimension, then reduce the storage space, and finally reduce the computational complexity. However, the disadvantage of this method is that it loses the original score information and is easy to produce overfitting. Gong et al. [17] adopted clustering algorithm to alleviate the problem of data sparsity to a certain extent. However, the disadvantage is that the difference of users' interests is not reflected enough, and the accuracy of recommendation is difficult to ensure. Xanat et al. [18] put forward an online video content recommendation system following the principle of sustainable design and application, increased the classes and methods of recommended items, and considerably enriched the extracurricular English reading resources. However, this sys-

tem encountered problems like low content matching accuracy. Tripathi et al. [19] raised an intelligent video recommendation engine system considering personalized emotions and used on-policy and off-policy (Q-learning) temporal difference learning techniques. The objective was to train DBRNN to learn context patterns on the RL scenario and efficiently generate new video sequences, thus reaching the goal of recommending diversified English videos. However, the recommended contents were excessively dispersed and lacked pertinence.

Personalized English teaching methods and systems specific to college students have been explored by research scholars. These systems provide reference and basis for personalized English teaching among college students and effectively meet the personalized needs of college students for college English teaching to some extent. With the extremely abundant Internet resources in the contemporary era, the above-mentioned methods have the ability to automatically recommend English teaching videos. However, the contents recommended are too general, and the search methods cannot satisfy the personalized English learning needs of contemporary college students. Hence, designing an optimized automatic recommendation system of college English teaching videos is necessary to meet the English teaching demands of contemporary college students.

3 Methodology

3.1 Automatic recommendation system architecture of college English teaching videos

The Java EE system was used as the overall architecture (Fig.1) of the automatic recommendation system for college English teaching videos. This system was mainly composed of three layers: interface layer, business logic layer, and data layer, where the interface layer mainly connected the internal and external servers, through which students could log in to the system to search for the recommended list of English teaching videos. The business logic layer was the core of this system, which integrated the recommendation algorithm and implementation of relevant functions of information. It aimed to administer student information and video resources. The data layer was mainly used to store the system business data and application information and provide students with a large number of classified video databases. Additionally, it could help students realize fuzzy search and accurate retrieval.

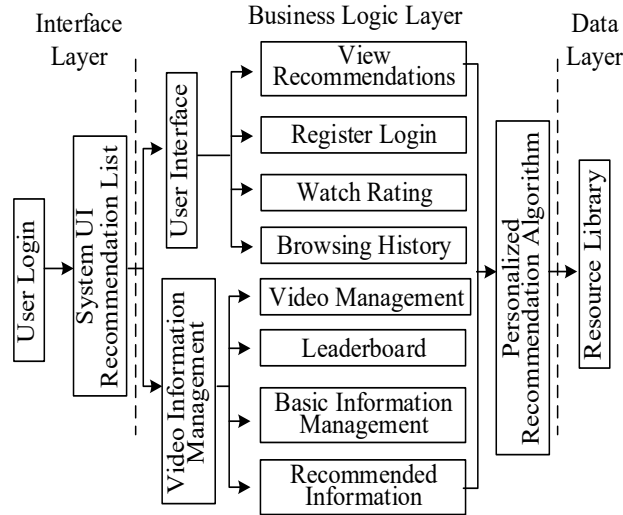


Fig. 1. Schematic diagram of the automatic recommendation system structure for English teaching videos

3.2 Design of video management module

The operating authorization of the video management module at the business logic layer was only restricted to the administrator, who added, deleted, or altered the uploaded teaching videos. Fig.2 shows the structure of the teaching video resource management module.

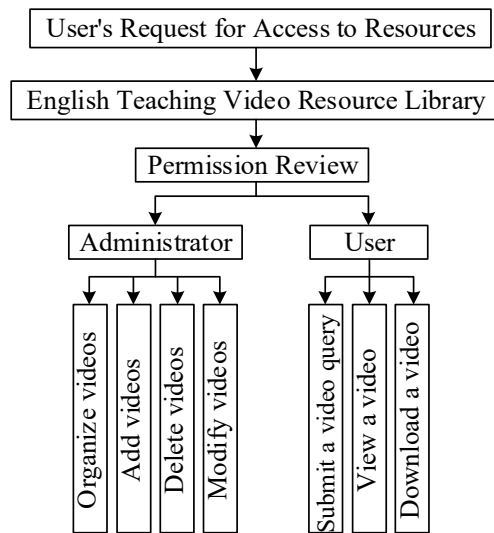


Fig. 2. The header image of online-journals.org

- **Add English teaching videos:** After logging in to the system at the terminal, the administrator edits video resources, type videos into the system after the review, and then it can perform the later deletion or alteration according to the added video names. The basic function of automatic video recommendation system is the addition of video resources. Furthermore, it integrates the function of selecting the video class and the ability of solving the client-side compatibility. After being added into the system, new videos will be saved in the database to generate a new list, which records the detailed information of videos, such as name, class, and duration.
- **Delete English teaching videos:** If the video does not obtain enough attention, the video is valueless and should be deleted by the administrator. If several teaching videos are valueless, they could be deleted in batches to improve the work efficiency of the administrator.
- **Alter teaching videos:** In case of any change in video resources, the administrator should alter the videos in a timely manner to ensure the accuracy of information in all videos and to keep the single resource information consistent with the database information.
- **Design inquiry function:** The inquiry function provides convenience for students. Although all teaching video resources in the system are managed after the classification, inquiring according to the given classes in the system under better resource information will take a long time. To save time and improve the system applicability, keyword search according to students’ personalized demands is recommended. Only necessary key fields should be input to retrieve the video database, to screen out related video resources and meet students’ demands for viewing or downloading.

3.3 Automatic recommendation of college English teaching videos

Mining of personalized demand information. The information video information meeting students’ personalized demands depends on students’ interests in the videos. Therefore, the degree of interest in videos can be effectively judged according to students’ browsing history for English teaching videos [20]. During the video learning process, each resource simultaneously contains the resource itself and resource profile, and the degree of interest is calculated according to the content features included. Assume that the total number of times of browsing one video is A , the duration of single browsing is T , the total number of bytes is B , and video content coefficient, class coefficient, and profile coefficient are α , η , and β , respectively. Before students’ interest in this teaching video is calculated, the interest in browsing the video content and profile should be first solved. The calculation formula of interest in video content is provided below:

$$K^a = \eta \times \alpha \times \sum_{i=1}^n \frac{T_i^a}{B^a} \quad (1)$$

Where n is the number of browsing times; T_i^a denotes the duration of browsing for the i (th) time; and B^a stands for the total number of content bytes.

The interest in video profile is obtained through the following calculation formula: where represents the number of browsing times; is the duration of browsing for the (th) time; and is the total number of profile bytes.

$$K^b = \beta \times \sum_{i=1}^m \frac{T_i^b}{B^b} \tag{2}$$

where m represents the number of browsing times; T_i^b is the duration of browsing for the i (th) time; and B^b is the total number of profile bytes.

$$K = K^a + K^b = \eta \times \alpha \times \sum_{i=1}^n \frac{T_i^a}{B^a} + \beta \times \sum_{i=1}^m \frac{T_i^b}{B^b} \tag{3}$$

Students’ interest in this video resource is:

$$I = \frac{KN}{\sum_{j=1}^N K_j} \tag{4}$$

where N is the total number of English teaching videos. When $I \geq 1$, the video is of interest; otherwise, it is of no interest.

The teaching video information that meets students’ personalized demands was established through the acquired degree of interest, and then the system classified the videos according to this information.

Automatic recommendation of teaching videos. The teaching video information that meets students’ personalized demands was established through the acquired degree of interest, and then the system classified the videos according to this information.

The essence of automatic recommendation of English teaching videos based on personalized demand is to classify according to video records browsed by students. Therefore, videos that have been viewed were set as the sample set to automatically classify videos [21]. Naïve Bayes is a classification method featured by simple structure, accurate classification, fast operation, and stable performance [22, 23]. The sample-set was set as C , containing x classes, and $C = \{c_1, c_2, \dots, c_m\}$, y is the attribute value contained by single samples, and then $D = \{d_1, d_2, \dots, d_n\}$. The eigenvector was $E = \{e_1, e_2, \dots, e_n\}$, and the posterior probability is calculated through the following formula:

$$K(c_i|E) = \frac{K(c_i) \times K(E|c_i)}{K(E)} \quad (5)$$

where $K(E)$ is a constant that represents all classes. Formula (5) was simplified according to the concept of maximum likelihood hypothesis:

$$K(c_i|E) = K(c_i) \times K(E|c_i) \quad (6)$$

The viewed videos were classified into class c_1 (interest) and class c_2 (disinterest) according to the mined personalized video demand information [24]. A training set was constructed according to the extracted video resource eigenvector. If the new teaching video F was not classified or described, its eigenvector was built as $F = \{f_1, f_2, \dots, f_n\}$. The class probability of video F was calculated by using formula

(6). The probability of class c_1 was calculated by using formula 7:

$$K_1 = K(c_1|F) = K(c_1) \times K(F|c_1) \quad (7)$$

The calculation formula for the probability of class c_2 is as below:

$$K_2 = K(c_2|F) = K(c_2) \times K(F|c_2) \quad (8)$$

The total amount of class c_1 video resources was set as M_1 and that of class c_2 video resources as M_2 , and their prior probabilities are respectively as follows:

$$K(c_1) = \frac{1 + M_1}{2 + M_1 + M_2} \quad (9)$$

$$K(c_2) = \frac{1 + M_2}{2 + M_1 + M_2} \quad (10)$$

The probabilities of class c_1 and class c_2 were calculated according to formulas (9) and (10):

$$K(F|c_1) = \prod_{i=1}^n K(f_i|c_1) = K(f_1|c_1) \times K(f_2|c_1) \times \dots \times K(f_n|c_1) \quad (11)$$

$$K(F|c_2) = \prod_{i=1}^n K(f_i|c_2) = K(f_1|c_2) \times K(f_2|c_2) \times \dots \times K(f_n|c_2) \quad (12)$$

The total eigenvector of video F was set as $|G|$, the total number of times for f_i to appear in class c_1 was $HT(f_i, c_1)$, and that for it to appear in class c_2 was $HT(f_i, c_2)$, and then the class attribution probabilities of video F are respectively as follows:

$$K(F|c_1) = \frac{1 + HT(f_i, c_1)}{|G| + \sum_{i=1}^{|G|} HT(f_i, c_1)} \tag{13}$$

$$K(F|c_2) = \frac{1 + HT(f_i, c_2)}{|G| + \sum_{i=1}^{|G|} HT(f_i, c_2)} \tag{14}$$

According to the calculated interest probabilities of class c_1 and class c_2 , if $K_2 < K_1$, then this video is of interest; otherwise, it is not of interest. According to the judgment results, the system automatically recommended the college English teaching videos to students with personalized demands.

4 Results and analysis

College sophomores who major in English were taken as the test objects. The English teaching video browsing records of eight students were randomly chosen to generate the test data, the videos they were interested in were already collected videos, and the videos of no interest were already recycled videos. The eigenvector was extracted according to the video content and profile, and a test dataset was established using this eigenvector. Table 1 lists the test dataset information of English teaching videos.

Table 1. English teaching video dataset

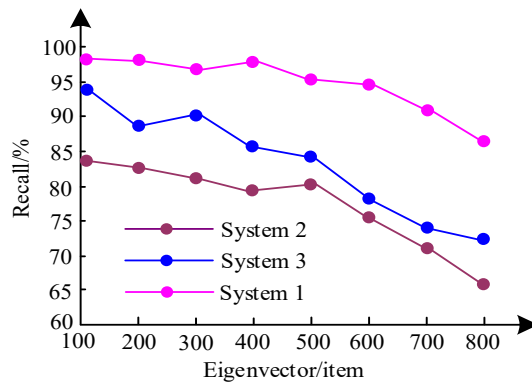
Student	Item of interest	Item of no interest
A	324	265
B	312	521
C	365	304
D	402	226
E	255	400
F	365	152
G	387	378
H	396	253

Table 2 shows the personalized demand mining test implemented according to the browsing record of each student. The average correctness of interest in students’ personalized demand information mining was 90.57% and that of disinterest was 85.64%. This result indicates that the established system could meet students’ demands for the automatic recommendation of English teaching videos.

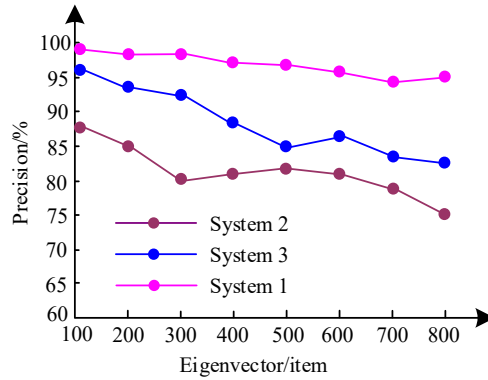
Table 2. Mined results of English teaching videos

Student	Items of interest			Items of no interest		
	Total number of mined items	Number of correct items	Correctness	Total number of mined items	Number of correct items	Correctness
A	345	304	88.12%	248	205	82.66%
B	321	301	93.77%	565	515	91.15%
C	357	312	87.39%	350	289	82.57%
D	435	398	91.49%	198	158	79.80%
E	305	268	87.87%	352	308	87.50%
F	387	362	93.54%	201	169	84.08%
G	369	329	89.16%	358	323	90.22%
H	325	303	93.23%	265	231	87.17%

The performance of the proposed system was compared with that of the intelligent recommendation system (system 2) on the basis of the optimization algorithm of the multi-classification support vector machine [7] and the collaborative filtered video recommendation system (system 3) based on video content detection [8]. First, the dataset was utilized to compare the recall ratio and precision ratio of video information, and the test results are shown in Fig.3. Compared with the two systems, the average recall ratio of the proposed system was 95.18%, which was 17.52% and 11.11% higher than those of system 2 and system 3, respectively. Its average precision ratio was 97.2%, which was 25.6% and 8.51% higher than those of system 2 and system 3, respectively. This result indicated that the proposed system has a stronger ability for the personalized automatic recommendation of teaching videos.



a) Recall ratio of automatic video recommendation



b) Precision ratio of automatic video recommendation

Fig. 3. Comparison of the performance of the three systems

Students usually tended to accept top-ranked contents in the recommendation list of the teaching videos recommended by the system. Therefore, the top 16 recommended videos were used for the analysis and discussion, and the average ranking degree was used to comparatively test the recommendation accuracy, as shown in Fig.4. With the increase in the number of videos in the recommendation list, the average ranking degree of the three recommendation systems presented a gradual rising trend, resulting in the continuous decline of video recommendation accuracy. Although the average ranking degree of the proposed system showed a weak declining trend, compared with system 2 and system 3, it reached the highest automatic recommendation accuracy for teaching videos. Therefore, the proposed system could effectively recommend English teaching videos to students according to their personalized demands.

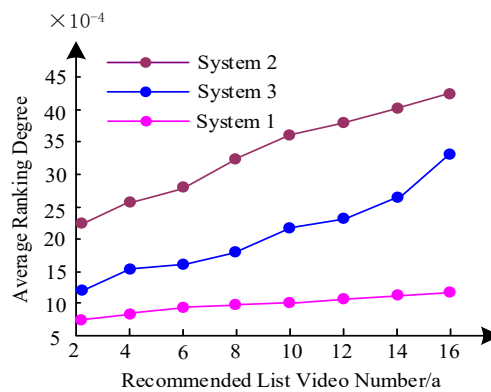


Fig. 4. Comparison of recommendation accuracy

In the era of diversification, students should accept information with diversified elements. Likewise, the teaching contents recommended by the system should not be

too similar. Instead, they should be diversified and novel not only to meet students’ demands for knowledge but also to conform to current developments. A comparative test was conducted using the abundance of teaching video contents automatically recommended by the system, as shown in Fig.5. As the quantity of videos in the recommendation list increased, so did the abundance of contents recommended by all the three systems. However, when the quantity of recommended videos was small, their difference in the abundance of video contents was not evident. With the increase of video contents, such difference became increasingly obvious. The results showed that the teaching videos recommended by the proposed system contained the richest contents and catered more to students’ diversified demands for knowledge.

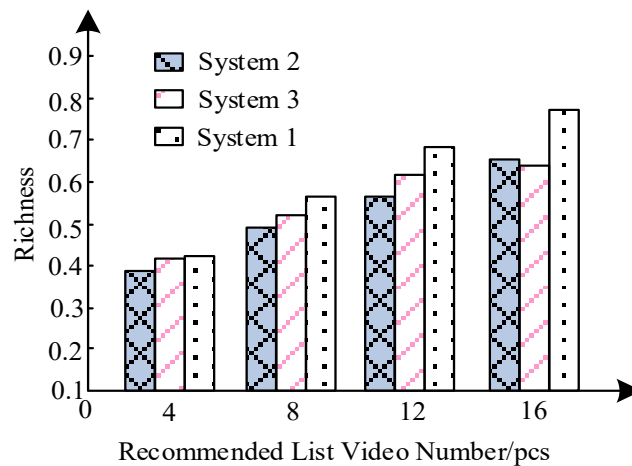


Fig. 5. Comparison of diversification in recommended videos

A good system should not only be of favorable applicability but also strong operability. The three systems were compared in terms of their operational stability, as shown in Fig.6. The operational stability of the three systems changed to different degrees with the increase of teaching videos. The proposed system reached the highest stability coefficient (1.06) under approximately 400 videos. Before 450 videos were output, the stability coefficient was kept at a stable status with minor fluctuations. However, the highest stability coefficients of systems 2 and 3 were only 0.73 and 0.65, respectively, and their fluctuations in the operation process were large. These results indicate that the automatic recommendation system of college English teaching videos based on students’ personalized demands had the best operational stability.

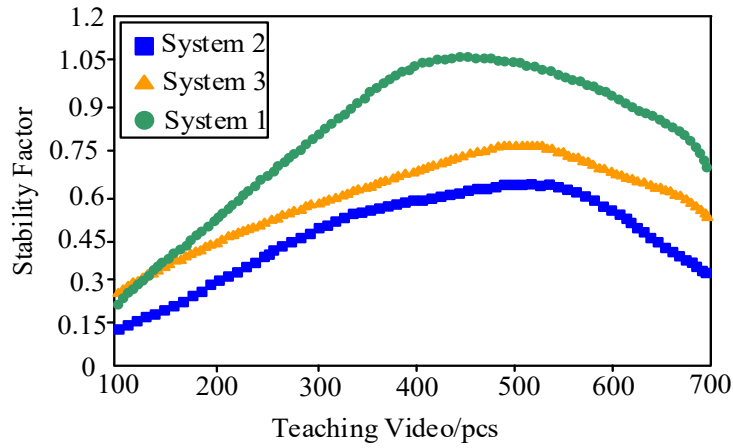


Fig. 6. Comparison of system stability

All test objects were averagely divided into three groups to carry out the experiential operation of the three systems, in an effort to collect students' evaluation of four aspects: system applicability, satisfaction with recommendation, operational convenience, and content integrity. Fig.7 shows the results. The proposed system received the best comments from all aspects, and the overall average applause rate was 97.79%, which is 4.47% and 4.04% higher than those of system 2 and system 3, respectively. The superiority of the proposed system was proven through the test of practical application effect, which showed high student satisfaction and high practical application value.

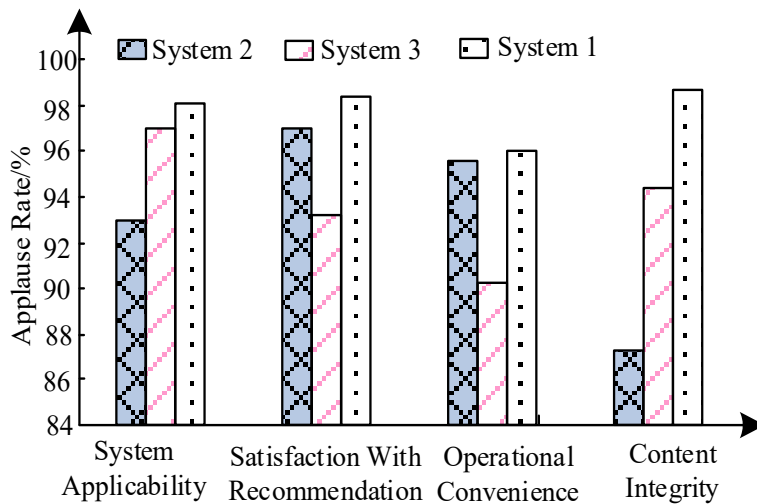


Fig. 7. Survey results of system applause rate

5 Conclusion

In recent years, colleges and universities have integrated personalized demands into students' daily learning. Learning based on personalized demands has already become the mainstream trend of educational development. Based on students' personalized demands, an automatic recommendation system of college English teaching videos was constructed, and the following conclusions were obtained:

Personalized information was mined according to students' video browsing history. The information mined was used to classify the videos into two classes (interest and disinterest) by the naïve Bayesian method. The video class was judged through the video classification probability. On basis of the judgment results, the system can automatically recommend the college English teaching videos to students according to their personalized demands.

The test results show that the proposed system is capable of automatically recommending teaching videos to students according to their personalized demands, and the video contents it contains are diversified and novel. Moreover, it can reach high recommendation accuracy and acquire high satisfaction with the experience. This system extends the new idea for the automatic recommendation of personalized learning.

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