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RESEARCH ARTICLE

Teaching Design Model of Media Courses Based on Artificial Intelligence

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ABSTRACT Under the background of information technology, in order to promote the smooth development of teaching design of media courses, we must adhere to the basic principle of taking students as the center and reasonably create teaching situations. Insert high-flying wings for the production and dissemination of intelligent media content in the AI era, making content production faster and more efficient, realizing scene and experience of content terminals, and making information dissemination more intelligent and personalized. This topic launches the teaching design of media courses based on AI (artificial intelligence). The teaching scheduling model of media courses and the teaching recommendation algorithm of media courses based on AI are established. By introducing LSTM (Long Short-Term Memory) to embed the multi-feature information of users and courses into the model, users' interests and preferences can be fully understood, and satisfactory recommendation results can be given. The results show that the accuracy of CF(collaborative filtering) recommendation based on clustering is higher than that of this recommendation algorithm. The accuracy and recall of this recommendation algorithm can reach 91.4619% and 87.7128% respectively. On the one hand, the cold start problem of CF algorithm is improved, on the other hand, compared with the content-based recommendation algorithm, the effect is significantly improved, and the expected effect is achieved.

INDEX TERMS Artificial intelligence, media courses, teaching design, recommendation algorithm.

I. INTRODUCTION

Amidst the ongoing societal progress and rapid scientific advancements, information technology has seamlessly integrated into our daily lives and diverse industries [1]. This technological revolution has not only revolutionized our way of life but has also transformed the global landscape [2]. Currently, artificial intelligence (AI) stands at the forefront of China's technological development, playing a pivotal role in sectors like finance, transportation, healthcare, entertainment, and manufacturing [3]. Within the education sector, AI technologies such as big data, algorithms, machine learning, and deep learning have introduced personalized learning, intelligent tutoring systems, and other innovative teaching methods, exerting numerous positive impacts on educational activities [4], [5], [6]. The evolution of AI has profoundly influenced not only our daily lives, studies, and work but also university teaching methodologies and students' learning patterns [7].

The intelligent media landscape is evolving at a breakneck speed. In comparison to media students, employers in the media industry prefer candidates with an interdisciplinary background proficient in data search, quantitative analysis, and content distribution [8]. Therefore, in designing future media courses, educators must adapt and abandon outdated teaching methods and ideologies, effectively integrating information technology into all aspects of media course design, showcasing its practical value and significance [9], [10], [11]. Foreign universities have excelled in educational informatization, with most renowned institutions in western developed countries completing the transition to digital campuses, fully networked schools, and advanced auxiliary teaching systems [12], [13]. Ying and Jiaxuan designed a curriculum scheduling system leveraging the software process method and relevant specifications,

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encompassing demand analysis, overall design, application design, and more [14], [15], [16]. AI addresses practical course scheduling challenges, utilizing a range of AI technologies to develop a comprehensive scheduling system that integrates knowledge, reasoning, and decision-making. Liang defined the relationships between lesson elements involving teachers and natural classes, introducing a computer-based course scheduling algorithm centered on correlating lesson elements and calculating candidate time-space slices [17]. Wang et al. analyzed the fundamental principles of course scheduling management, defining the interrelationships among teachers, time, and space, and realizing an intelligent course scheduling algorithm through defining conditions, calculations, and constraints related to candidate time and space [18], [19], [20]. Zheng et al. set objectives, utilizing LSTM (long short-term memory) to predict achievements and recommend courses based on target outcomes. They employed graph volume networks to model course selection sequences, learning preference information [21]. Wang et al. designed a sequential recommendation task model by enhancing the recurrent neural network, demonstrating the significance of long-term dependencies in sequential tasks [22].

Media courses center on application technology rather than development technology. Embracing this concept is crucial for fostering professional confidence and awareness. In this cognitive framework, AI thinking prevails in news dissemination [23]. Universities educating media professionals must adapt to fresh changes and transformations. Consequently, media programs, as the endpoint of this training, will undergo curricular adjustments. Innovative curriculum systems, such as "AI+ courses" and interdisciplinary offerings aligned with contemporary trends, will disrupt traditional media program structures [24], [25].

The surge in internet growth has sparked a significant rise in demand for online education, presenting an opportunity amidst advancing information technology. To aid online learners in pinpointing relevant course resources, the course recommendation system emerged. This system tailors course suggestions to users' unique traits and interests. Hence, refining and enhancing algorithms that consider users' characteristics, analyze their behaviors, and deliver personalized course recommendations is imperative. In sum, this study carries substantial theoretical and practical significance.

II. RESEARCH METHOD

A. DESIGN OF COURSE SCHEDULING MODEL FOR MEDIA COURSES

In the realm of information technology, fostering the seamless progress of media course designs demands adhering to a student-centered approach and crafting engaging teaching scenarios. Nowadays, the complexities arising from intelligent technology and media advancements undermine established media theories, rendering traditional media frameworks inadequate in explaining issues stemming from intelligent media's societal operations and sources of power [26]. In essence, intelligent media convergence poses challenges to prevailing media ethics and disrupts existing media paradigms. In the AI era, intelligent media content production and dissemination soar to new heights, enhancing speed, efficiency, and personalization while realizing immersive content experiences [27].

The intelligent course scheduling system emerges as a pivotal component in modernizing the entire teaching management infrastructure. This upgrade encompasses various aspects, including system architecture enhancement, mobile service delivery, dynamic resource allocation, digital teaching resources, and intelligent demand sensing [28]. Traditional teaching resources, pre-set according to semester-start plans, are giving way to internet-enabled teaching practices, diversifying student learning paths, and introducing uncertainty in classroom resource utilization for face-to-face instruction [29]. Consequently, static course scheduling systems rooted in face-to-face teaching are inadequate for today's blended learning environments that combine online and in-person instruction. Therefore, evolving the course scheduling system is imperative for dynamic resource allocation and information optimization.

Our design principles align with system requirements, emphasizing an open system, functional diversity, and a modular structure. The open system fosters continuous functionality updates and seamless integration into educational administrative systems. Modular design underpins system openness and diversity, facilitating effortless updates [30]. The course scheduling process aims for intelligence, minimizing manual intervention while ensuring reasonable outcomes. It allows operators to adjust course schedules on-screen as needed. Leveraging the parallels between multi-agent systems and course scheduling, we prioritize classes, treating teachers, classrooms, time slots, and courses as resources. This approach involves multiple classes competing for resources, contrasting with traditional methods of searching for courses.

The intelligent teaching system represents an integrated wireless learning terminal solution. It requires the collaboration of mobile learning terminals, servers, and teacher control programs over a wireless network [31]. This encompasses hardware components like learning terminals, servers, teacher devices, and wireless network connections, alongside the development of a three-terminal software system and the integration of software and hardware application environments. The teacher-side system adopts a B/S (Browser/Server) structure, aligning with contemporary informatization trends characterized by efficiency, security, and convenience [16]. The system's topological framework is illustrated in Figure 1.

In our research, the teaching scheduling of multimedia courses is realized by an algorithm that comprehensively considers factors such as student schedule, teacher availability and teaching resources. Firstly, the algorithm will analyze students' free time and teachers' teaching plan to ensure

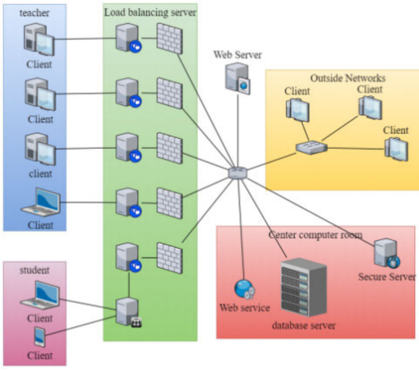

FIGURE 1. Topological relationship among system objects.

that the curriculum arrangement will not conflict with other activities of students or other teaching tasks of teachers. Then, the algorithm will prioritize the courses according to their nature, importance and prerequisites. In addition, we will use historical data and prediction models to optimize the course schedule to maximize students' learning efficiency and satisfaction.

Timetable arrangement refers to the linear programming problem that combines the mutual planning of teachers, time and space, students and courses into a five-in-one to obtain the final solution [32], [33]. In essence, the curriculum arrangement of educational administration realizes the nonlinear, multi-objective solution optimization, and the combination of time and space elements does not conflict with each other to obtain the best solution. The expected goal of the educational administration of intelligent curriculum arrangement and the demand of curriculum arrangement are based on the constraints, which is conducive to students' study and teachers' teaching.

Fuzzy clustering is to calculate the similarity between data points and assign the membership degrees of data points to different clusters based on these similarities. Fuzzy C-means clustering algorithm is adopted, which determines the membership degree of each data point to all clusters through iterative optimization process, thus forming the final fuzzy clustering result. In order to realize the idea of reasonable automatic course arrangement in educational administration, it is necessary to realize the automatic course arrangement with constraints by means of software programming. The intelligent course arrangement problem is described as a mathematical modeling model as the basic structure, with a total of n abstract numbers of courses $S\,(S_1, \cdots S_n)$, each course corresponding to a set of C_i classes, and any on-the-job teacher can teach this course.

The available classroom set is expressed as $R\,(R_1, \cdots R_n)$, and the number of classrooms is n abstract, and each classroom can accommodate $(X_1, \cdots X_n)$ people.

This system adopts an active negotiation strategy, which is suitable for the situation that the security system provides enough security capability. On the basis of ensuring the safety of both parties, the negotiating parties can complete the negotiation task through concessions. The negotiation model adopts a resource-based negotiation strategy. In the process of negotiation, negotiation resources are represented by various security policies. Incremental concessions are shown in formula (1):

$$f\,(t_{next}) = a_{start}\frac{1/m_{left}}{1/m_{start}} + f\,(t_{current}) \tag{1}$$

where a_{start} represents the initial concession range, m_{left} represents the number of strategies that have not been negotiated in the current state, m_{start} represents the number of initial negotiation strategies, $f\,(t_{next})$ represents the suggested value at the next moment, and $f\,(t_{current})$ represents the current suggested value.

Declining concessions are shown in formula (2):

$$f\,(t_{next}) = f\,(t_{current}) - a_{start}\frac{1/m_{left}}{1/m_{start}} \tag{2}$$

When the security policy negotiation of all node values is successful, the security policy negotiation can be successfully completed, otherwise the whole negotiation process will fail.

B. TEACHING RECOMMENDATION OF MEDIA COURSES BASED ON AI

Practicing ideological and political education in curriculum needs to keep pace with the times and innovate constantly in teaching methods. The so-called teaching method refers to ''the ways and means adopted by teachers and students in the common activities of the teaching process, including teaching methods and learning methods, in order to accomplish certain teaching tasks''. In the age of media convergence, the training task of media talents in information literacy, ability composition, thinking training, etc. has been difficult for the previous teacher-centered classroom teaching methods to be competent. Integration of multi-media and multi-teaching methods. In the training of media talents, this kind of teaching method, which has fusion characteristics, is conducive to the internalization of fusion thinking in a subtle way.

Recommendation system is a system that uses users' historical preferences and habits to recommend suitable information or goods to users. Through the filtering and screening of users' historical interactive projects, the user's project preferences are obtained, and personalized recommendation services are provided. Therefore, considering the rapid development of recommendation system in news, e-commerce and other fields, the recommendation system is applied to the online platform.

In the CF(collaborative filtering) recommendation algorithm based on users, in order to improve the efficiency of searching for similar users of target users, users are usually clustered according to their interests and preferences, and then similar users are found from the clusters to which users belong, thus narrowing the scope of searching for similar users [34]. The traditional CF recommendation algorithm does not take into account the changes of users' interests and whether the project is outdated, so it is difficult to obtain satisfactory recommendation results when it is directly applied to online course recommendation. To solve the appeal problem, firstly, this paper comprehensively considers users' feedback information about the project, mines users' interests from users' learning behavior data, and improves the user interest model, reduces the dependence on users' rating information, and improves the accuracy of user clustering.

This section fully combines the characteristic information of users and courses and the text information of courses, and introduces LSTM to predict users' ratings of courses, and further selects Top-N recommendation results. By embedding the multi-feature information of users and courses into the model, users' interests and preferences can be fully understood, and satisfactory recommendation results can be given.

Define user set $U = \{1, 2, \cdots, u\}$, course set $I = \{1, 2, \cdots, i\}$, target user u prediction score of course i is $p_{u,i}$, and e_k^u is used to represent the vector form after embedding feature K. The calculation formula of user feature vector matrix R_u is shown in (3).

$$R_u = \sum\nolimits_{k \in f_u} e_k^u \tag{3}$$

In order to simplify the task setting, we limit our attention to the first-order neighbors of the target learners. Then, apply a softmax function to normalize the coefficient:

$$a_{ij} = softmax\left(e_{ij}^u\right) = \frac{\exp\left(e_{ij}^u\right)}{\sum_{k \in N(i)}\left(e_{ij}^u\right)} \tag{4}$$

where $N(i)$ represents the neighbor of learner u_i.

Fuzzy clustering divides a given object into some equivalent classes by using fuzzy equivalence relation. This clustering method determines the similar classes of objects by a certain threshold, which makes the similarity between users belonging to the same class high, while the similarity between users in different classes is low [35].

It is more effective than traditional clustering. Use formula (5) to calculate the membership degree $\mu_j(y_i)$ of each user relative to a certain fuzzy cluster:

$$\mu_j(y_i) = \frac{\|y_i - n_j\|}{\sum_{k=1}^{k}(\|y_i - n_k\|)} \quad i = 1, 2, \cdots, n;\ j = 1, 2, \cdots, k \tag{5}$$

y_i represents the score vector of each user, n_j represents the score vector of the center of each fuzzy cluster, $\|y_i - n_j\|$ represents the similarity between user i and fuzzy cluster j, and k represents the number of fuzzy clusters.

A flexible negotiation strategy is adopted for students in different places and classes. First, collect students' needs and opinions through online surveys or face-to-face discussions. Then, teachers will adjust the teaching content and methods according to this information to ensure that all students can get the best learning experience. At the same time, the distance teaching platform is also used to promote real-time communication and cooperation between teachers and students, thus solving the communication problem in teaching in different places.

Through the input gate, the forgetting gate and the output gate, the influence of the t word on the $t-1$ word and the final output result of the t word in the LSTM network are calculated and controlled in the LSTM network. The output result h_t of the t word is as follows, and DP refers to the Dropout operation on the output result.

$$d = o_t \cdot \tanh(c_t) \tag{6}$$

$$h_t = DP(d) \tag{7}$$

Because the number of course learners in different categories will be quite different, it is of little significance to sort all the courses in the data set, so the sorting is conducted separately for the courses in each secondary category. After getting the sorted list, the following formula is used to calculate the feature value of the course popularity to be used finally:

$$pref_{hot}(u, i) = 1 - \frac{R_i}{N} \tag{8}$$

In our multimedia course design, backtracking times are mainly used to optimize the performance of recommendation algorithm. When the recommendation results are unsatisfactory or conflicting, the recommendation strategy is adjusted by backtracking, and the recommendation results are recalculated to ensure the accuracy and satisfaction of the recommendation.

N represents the total number of courses under the corresponding classification, R_i represents the ranking of course i, and $R_i = 1$ course is the course with the highest $pref_{hot}(u, i)$ value, that is, the relatively hottest course under this classification. After this step of calculation, we can get the feature value of course popularity ranging from 0 to 1.

The novelty of fuzzy clustering mainly lies in its ability to deal with fuzzy boundary problems between data points, allowing data points to belong to multiple clusters with different membership degrees. This method is especially suitable for dealing with fuzzy and overlapping data such as students' interests and preferences in media courses. By introducing fuzzy logic, this algorithm can capture and reflect these complexities and diversities more accurately. The flow chart of LSTM course recommendation algorithm proposed in this section is shown in Figure 2:

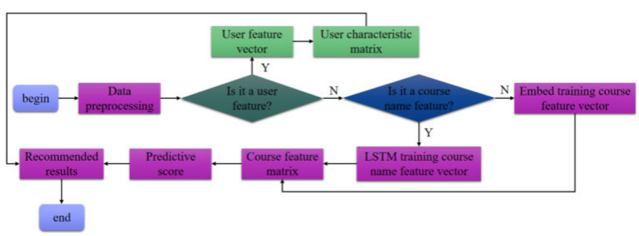

FIGURE 2. Flow chart of course recommendation algorithm.

This intelligent teaching system adopts an advanced architecture, including user interface layer, business logic layer and data storage layer. Through natural language processing and machine learning technology, the system can analyze students' learning behaviors and preferences, thus providing them with personalized learning resource recommendations. In addition, the system also integrates intelligent question answering function, which can automatically answer students' questions or guide them to find relevant resources. In practical application, the system is continuously optimized and improved according to the feedback from students and teachers to ensure that it can better meet the teaching needs.

III. ANALYSIS AND DISCUSSION OF RESULTS

The software of intelligent course arrangement management business system in universities has been written and realized, and will be put into trial operation soon. In order to further improve the function of the intelligent course arrangement system, the test work is put forward. In order to complete the test work better, the test plan should try to correct the found errors before the software goes online and runs, check whether the data is correct or not, and check the course arrangement function. In our research, we used a real data set containing multi-dimensional information such as students' interests and curriculum characteristics. The data set is collected through questionnaires, student behavior logs and other ways, aiming at comprehensively reflecting students' learning situation and interest preferences in media courses.

Conventional testing methods include performance testing, load testing, stress testing, configuration testing, concurrency testing, reliability testing, failure recovery testing and other testing items. Therefore, according to the test requirements, the testers formulated the concurrent performance test strategy, built the corresponding test environment and formulated the corresponding test cases.

When the test process reaches the expected result, the input value is given gradually by round test and backtracking test, and the results are observed and displayed. Table 1 Statistical analysis results of software round test.

TABLE 1. Statistical analysis of software round testing.

Project	First round test	The first round of regression test	Second round of regression test
Fatal error	11	8	0
Serious error	12	9	0
General error	16	11	0
Suggestion error	15	7	0

In this paper, whether the number of backtracking has an impact on the algorithm of this paper is tested and analyzed. Below, we test the impact of two different data, 100 students and 1000 students, on the number of backtracking. From the following Figure 3, we can clearly see that the number of students is in direct proportion to the number of backtracking.

In this paper, a personalized course recommendation algorithm based on clustering is proposed to cluster the students' grades, and its purpose is to guide students to choose

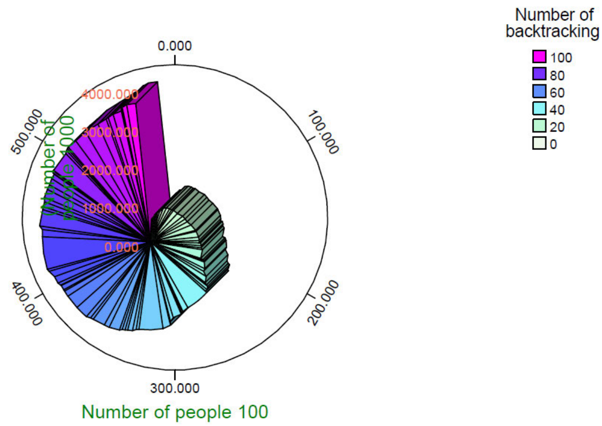

FIGURE 3. The influence of backtracking times on the results of course scheduling algorithm.

courses that can improve their ability. There is an essential difference between university course recommendation and commodity recommendation: the recommended courses should not only consider the students' own interest characteristics, but also meet the requirements of professional planning for students' ability.

The data set used in this experiment comes from the historical data of undergraduates who have undergone desensitization and other security treatments in the business system of a university. These data include 17,504 pieces of students' professional background information, 688,968 historical test scores and 1,674,351 book borrowing records. Through word segmentation technology, we extract the key words from the syllabus to construct the curriculum relationship model. Therefore, for the syllabus, we need the course description information, teaching objectives, and the specified textbooks, and also need to store the keyword groups that describe the course. We store data in a database, and this article uses MySQL to store data.

In terms of parameter setting, set LSTM network hidden layer dimension to 128, batch_size to 300, dropout to 0.5, learning efficiency to 0.005, course feature embedding vector dimension to 5, 80% of experimental data set as training samples and 20% of data as test samples.

To verify the performance of the algorithm proposed in this paper, the changes of MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) indexes of LSTM algorithm with the increase of iteration times are studied on the experimental data set according to different iteration times. By calculating the RMSE between the predicted score and the actual score, the accuracy of the recommendation algorithm can be quantified. In the research, we constantly optimize the algorithm to reduce RMSE, thus improving the accuracy of recommendation. The results are shown in Figures 4 and 5.

According to the experimental results, with the increase of iterations, the MAE and RMSE values of the recommendation algorithm based on LSTM proposed in this paper

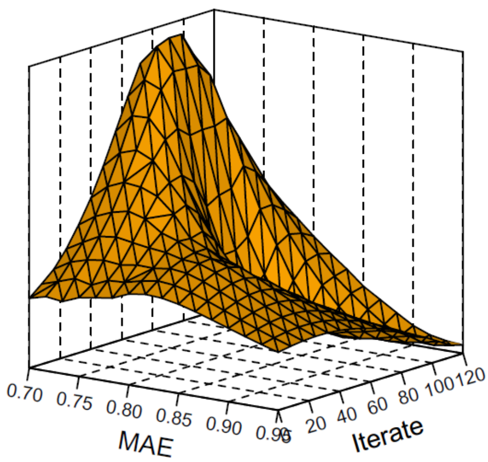

FIGURE 4. MAE curve with iteration times.

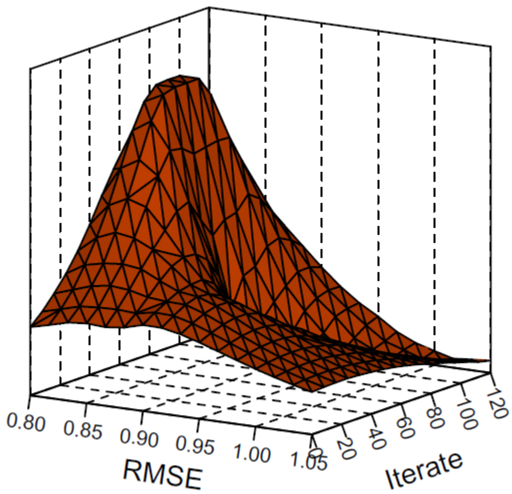

FIGURE 5. RMSE curve with iteration times.

gradually decrease and tend to be stable. When the number of iterations reaches 120, these two indicators are stable at 0.7016 and 0.8214 respectively. The data shows that the model has fully learned the inherent laws of the data at this time and gradually converges, and the subsequent iterations have limited impact on performance improvement. Compared with other algorithms, our algorithm shows a lower RMSE value in most cases, which proves its superior prediction accuracy and recommendation ability. Therefore, considering the model performance and computational efficiency, the maximum number of iterations in the training process is set to 120 to ensure that the algorithm has good computational efficiency while maintaining high accuracy. By comparing the RMSE performance of different algorithms, it is found that our algorithm has a lower RMSE value in most cases, which shows that the recommendation algorithm has advantages in accuracy.

Theoretically, the content-based algorithm can exert its effect no matter how many users' learning records, while the CF-based algorithm will perform better and better with the increase of users' learning data. The comprehensive recommendation algorithm proposed in this paper comprehensively considers these two algorithms, and it should have better performance when the number of users' learning is different. In order to verify this point, we calculate the accuracy and recall rate of the four recommendation algorithms, and analyze the accuracy rate of the algorithm proposed in this paper by comparing with different recommendation algorithms. The experimental results are shown in Table 2, Table 3, Figure 6 and Figure 7.

TABLE 2. Accuracy of the algorithm (%).

Achievement interval	CF recommendation	Clustering-based recommendation	CF based on clustering	our
0-60	68.4866	67.7948	78.604	89.4603
60-70	69.1803	71.7945	71.8147	84.4891
70-80	68.3654	62.3105	76.8039	91.4619
80-90	75.4493	67.179	77.8016	86.5428
90-100	68.4036	66.2885	79.7211	85.1867

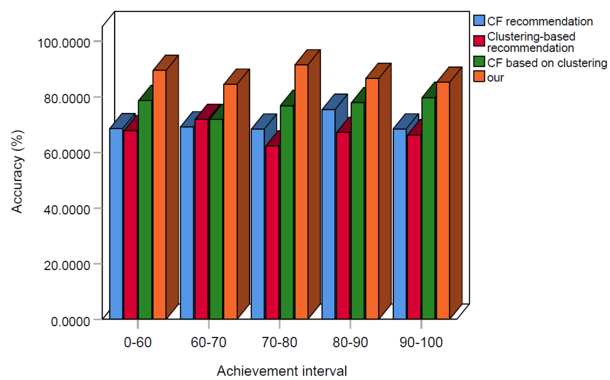

FIGURE 6. Statistical chart of accuracy of algorithm.

The comprehensive recommendation algorithm proposed in this paper shows excellent performance in multiple performance intervals. In the accuracy comparison in Table 2, the accuracy of this algorithm is generally higher than 80% in each score interval, especially in the 70-80 score segment, and the accuracy is as high as 91.4619%, far exceeding the other three recommended methods. In the recall data in Table 3, our algorithm continues to lead, especially in the score range of 70-80, the recall rate reaches 87.7128%, which shows high recommendation efficiency. These data fully prove that the comprehensive recommendation algorithm not only achieves a technical breakthrough by integrating collaborative filtering and content-based recommendation technology, but also

TABLE 3. The recall rate of the algorithm (%).

Achievement interval	CF recommendation	Clustering-based recommendation	CF based on clustering	our
0-60	64.8331	71.4594	70.8685	79.9328
60-70	63.2524	66.1666	76.0547	82.3297
70-80	62.9887	64.8601	68.5576	87.7128
80-90	66.1536	64.8893	68.2384	79.7745
90-100	70.1771	71.5703	71.7921	85.4735

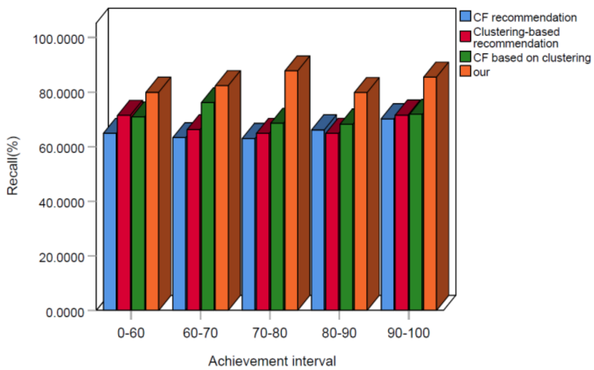

FIGURE 7. Statistical chart of recall rate of algorithm.

deeply embeds the features of users and courses by LSTM. More importantly, it can more accurately capture students' personalized needs and learning preferences, thus recommending courses that are more in line with students' actual preferences and learning status.

In this study, a recommendation algorithm based on LSTM is used to recommend personalized learning resources. The algorithm fully understands users' interests and preferences by embedding multi-feature information of users and courses, and gives satisfactory recommendation results. Compared with the recommendation algorithm of this paper, the CF recommendation based on clustering has higher accuracy, and the highest accuracy and recall rate of this recommendation algorithm can reach 91.4619% and 87.7128%. For students with poor grades, the effectiveness of the recommendation algorithm proposed in this paper is obviously better than the traditional CF recommendation algorithm based on clustering. In our multimedia course, fuzzy clustering technology is applied to analyze students' learning styles and interests. By collecting students' learning data and behavior patterns, students are divided into different groups by fuzzy clustering algorithm. In this way, teachers can make personalized teaching strategies and resource recommendations according to the characteristics and needs of each group. Practice shows that fuzzy clustering is helpful to improve the pertinence and effect of teaching, so that every student can get the most suitable learning resources and guidance.

With the increase of the number of users learning, more and more abundant user behavior data make CF algorithm perform very well. In practical application, we hope that the effect of personalized recommendation will be better and better with the passage of time, as users learn more and more courses. When the number of user courses changes, the overall effect remains at a good level. On the one hand, the cold start problem of CF algorithm is improved, on the other hand, compared with the content-based recommendation algorithm, the effect is significantly improved, and the expected effect is achieved. In this study, the diversity and complexity of students in media course learning are fully considered, and these data are processed by fuzzy clustering method to reflect the actual situation of students more accurately.

IV. DISCUSSION

With the rapid development of information technology, AI has gradually penetrated into all aspects of education, especially in the teaching of media courses. The teaching design model of media course based on AI proposed in this paper not only embodies the student-centered teaching concept, but also inserts high-flying wings for the production and dissemination of intelligent media content by reasonably creating teaching situations. This innovative attempt aims to make content production more efficient and realize the scene of content terminal.

In the traditional teaching mode, teachers often occupy a dominant position, while students are in a state of passive acceptance. However, with the support of AI technology, the teaching model proposed in this paper can make personalized teaching arrangements according to students' preferences. By introducing the LSTM model, the multi-feature information of users and courses is embedded in it, so as to understand the needs of users more comprehensively and give satisfactory recommendation results. This student-centered teaching method can not only stimulate students' learning enthusiasm, but also improve their learning effect.

The teaching scheduling model and recommendation algorithm of media courses based on AI established in this paper are innovative and practical. In the aspect of teaching scheduling, the model can dynamically adjust the teaching plan according to the students' learning progress to ensure the continuity of teaching. In the aspect of recommendation algorithm, although the results show that the accuracy of CF recommendation based on clustering is slightly higher than the recommendation algorithm proposed in this paper, the accuracy and recall of the latter still reach 91.4619% and 87.7128% respectively, showing good performance. More importantly, the recommendation algorithm solves the cold start problem of CF algorithm to a certain extent, that is, it can still give relatively accurate recommendation results when there is less user behavior data. This is undoubtedly an important advantage for new users or newly opened courses.

However, no model or algorithm can be perfect. While affirming the achievements of this paper, we should also see some problems and shortcomings. For example, although LSTM model has advantages in processing sequence data, it may also lead to performance degradation due to over-fitting or improper parameter setting. In addition, although the recommendation algorithm proposed in this paper performs well in accuracy and recall, it may need further optimization when dealing with large-scale data sets or complex scenes. Therefore, future research can explore these aspects in depth.

With the continuous development and popularization of AI technology, the future media course teaching may present more diversified and personalized characteristics. For example, by using technologies such as VR and AR, a more immersive and interactive learning environment can be created for students. Through big data analysis and mining technology, students' learning needs and characteristics can be more accurately understood, thus providing them with more personalized teaching services. The development and application of these technologies will bring a broader space for the teaching of media courses.

V. CONCLUSION

The development of AI technology not only has an impact on life, study and work, but also has a profound impact on university teaching methods and students' learning behavior. Media courses are not development technology, but application technology. Only by returning to the concept of application technology can we have enough professional confidence and consciousness. Under the background of this cognitive structure, AI thinking is widely used in the field of news dissemination. This topic launches the teaching design of media courses based on AI. The teaching scheduling model of media courses and the teaching recommendation algorithm of media courses based on AI are established. The results show that the accuracy of CF recommendation based on clustering is higher than that of this recommendation algorithm. The accuracy and recall of this recommendation algorithm can reach 91.4619% and 87.7128% respectively. With the increase of the number of users learning, more and more abundant user behavior data make CF algorithm perform very well.

In our research, a Web-based media course recommendation system is implemented. The system adopts advanced machine learning algorithm and fuzzy clustering technology to provide personalized course recommendation for students. Through the friendly user interface and interactive design, students can easily browse and choose the courses they are interested in. In addition, a wealth of data analysis and visualization tools are provided to help teachers and students better understand the learning situation and improve the teaching effect.

In practical application, we hope that the effect of personalized recommendation will be better and better with the passage of time, as users learn more and more courses. When the number of user courses changes, the overall effect remains at a good level.

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