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Article

Research on the Development and Application of Multimedia Teaching Resources for Civic and Political Education Based on Artificial Intelligence

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Abstract: Good multimedia teaching resources are an important guarantee for the teaching quality of Civic and Political Education. Based on CATLM theory, this paper constructs an online teaching resources development model, then introduces a recommendation algorithm based on ALS collaborative filtering, predicts the knowledge resources that the current user may need through the user's historical behaviors and preferences, and guides the user to find the resources accurately, so as to realize personalized teaching resources recommendation. The article concludes with an empirical test using students majoring in Civic and Political Education in a teacher training college as the research object. From the results of the independent sample t-test of students' Civic and Political Education competence, it can be seen that the observed value of the t-statistic of the experimental class and the control class is 25.963, and the p-value is $0.000<0.05$. Civic and Political Education multimedia teaching resources based on Artificial Intelligence have a significant impact on the comprehensive Civic and Political Education competence of students.

Keywords: CATLM theory; ALS; collaborative filtering; multimedia teaching resources; civic education

1. Introduction

With the continuous development of the education system in colleges and universities, the ideological education, as its core component, is gradually moving towards a new stage of intelligent construction [1-2]. In this process, the introduction and application of artificial intelligence technology has made college students' civic and political education realize a profound transformation from traditional experience-driven to data-driven, and the education model of teacher-student co-construction has been gradually replaced by human-machine co-construction [3-6]. Artificial intelligence in civic and political education is no longer a simple application of technology, but has gradually developed into a new model of human-machine collaboration, especially the development of multimedia teaching resources for civic and political education based on artificial intelligence, which completely reverses the form of traditional civic and political teaching resources [7-10].

Civic and political education multimedia teaching resources refers to the multimedia civic and political education information materials that have been digitized and can be operated in multimedia computer or network environment, which can inspire students to find and process all kinds of information through independent, cooperative, and creative ways so that digital learning becomes possible [11-14]. Multimedia teaching resources make teachers no longer have only one textbook, but can access and utilize extremely rich teaching resources at any time, which greatly enriches the content of Civics teaching [15-17]. In this case, the content of classroom teaching is more colorful, the teaching process is more flexible and changeable, students have more opportunities for active exploration, enthusiasm has been improved to a certain extent, and the ability to explore has grown [18-20]. The addition of artificial intelligence, but also for the differentiated teaching to provide technical support, to facilitate the Civics teachers in the education and teaching process to better tailor the teaching, personalized Civics education [21-22]. Artificial intelligence has a powerful data search storage, high-speed encrypted computing and analysis of each person's existing knowledge level and learning needs, and then push personalized courses, and provide students with suitable learning methods and learning plans, which greatly improves the learning efficiency rate, but also makes the effect of the Civic and Political Education better [23-25].

Based on the cognitive-emotional theory of multimedia learning, the article firstly constructs an online teaching resource development model based on the cognitive-emotional theory of multimedia learning. Then, on the basis of the traditional ALS collaborative filtering recommendation algorithm, the similarity between users and teaching resources is calculated separately, and the ALS algorithm is applied to the developed model. Finally, 110 teacher-training students majoring in ideological and political education were taken as the research subjects, and these students were divided into 60 each of traditional and experimental classes for testing. The effect of the practical application of the method of this paper was tested by using SPSS software, taking the independent samples t-test, and entering the data corresponding to the relevant quantitative indicators.

2. Construction of a model for the development of multimedia teaching resources for civic and political education

2.1. Cognitive-Emotional Theory of Multimedia Learning

Online teaching and learning can optimize the cognitive process of learners by using multiple media combinations. Some theories have had an important impact on the study of multimedia learning, such as cognitive load theory (CLT), cognitive theory of multimedia learning (CTML). However, these traditional multimedia learning theories pay more attention to the cognitive ability of learners, and emotions are often neglected in the multimedia learning and teaching process. CATLM theory suggests that positive emotions triggered by the learning activity itself can promote the learner's affective motivation state, thus triggering deeper cognitive processing and improving learning outcomes. The effect of emotion on learning depends on how the emotional factor acts on the cognitive resource input of the learner during the learning process. The theory emphasizes that the important role of emotions and other factors in the multimedia learning process cannot be ignored, and the cognitive-emotional theory of multimedia learning is shown in Figure 1.

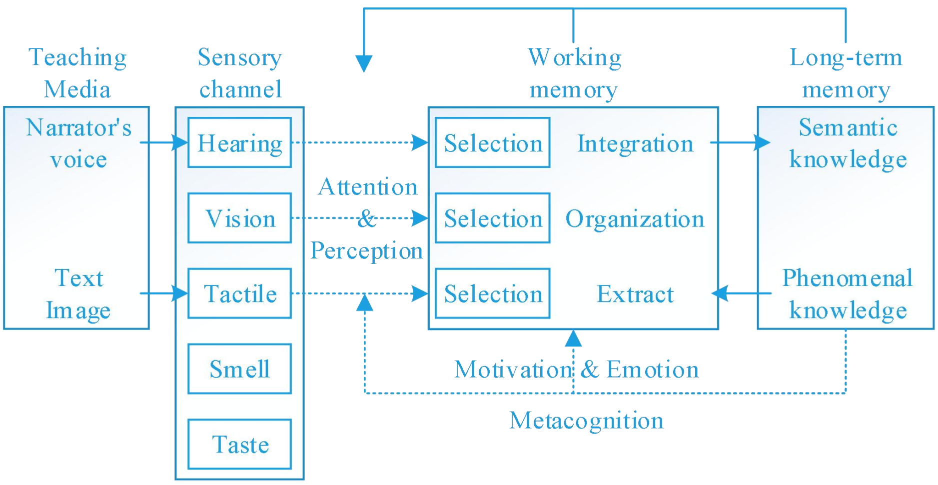

Figure 1. Cognitive and emotional theory of multimedia learning.

On the basis of this theory, the use of multimedia learning materials for emotional design has two effects: first, cognitive effects, which can promote the cognitive processing of learning materials. The second is the emotional role, which can affect the learner's feelings, attitudes and motivation towards the learning materials. Therefore, in the learning process, we should not only pay attention to the cognitive processing of learners, but also visually process the learning materials in order to influence the learners' emotion and inner drive, so as to comprehensively examine the role of learning effects.

2.2. The Construction of Civic Education Resource Development Model

The construction of the development model is centered on enhancing the application value of online teaching resources. Under the guidance of the value orientation of “stimulating positive emotions” and “optimizing learning effects” and the cognitive-emotional theory of multimedia learning, this study constructs an online teaching resources development model based on the literature review and survey research, and analyzes its characteristics. Based on the literature review and survey research, this study constructs an online teaching resource development model based on CATLM theory and analyzes its characteristics.

2.2.1. Modeling

Online education is committed to providing teachers and students with appropriate teaching resources to ensure the smooth development of teaching activities. The model takes the four stages of topic selection, design, production and evaluation as the development process, and carries out the emotional design from the internal layer, the behavioral layer and the reflection layer in three dimensions, which constitutes a "four-stage, three-dimensional" online teaching resources development model, and the online teaching resources development model is shown in Figure 2.

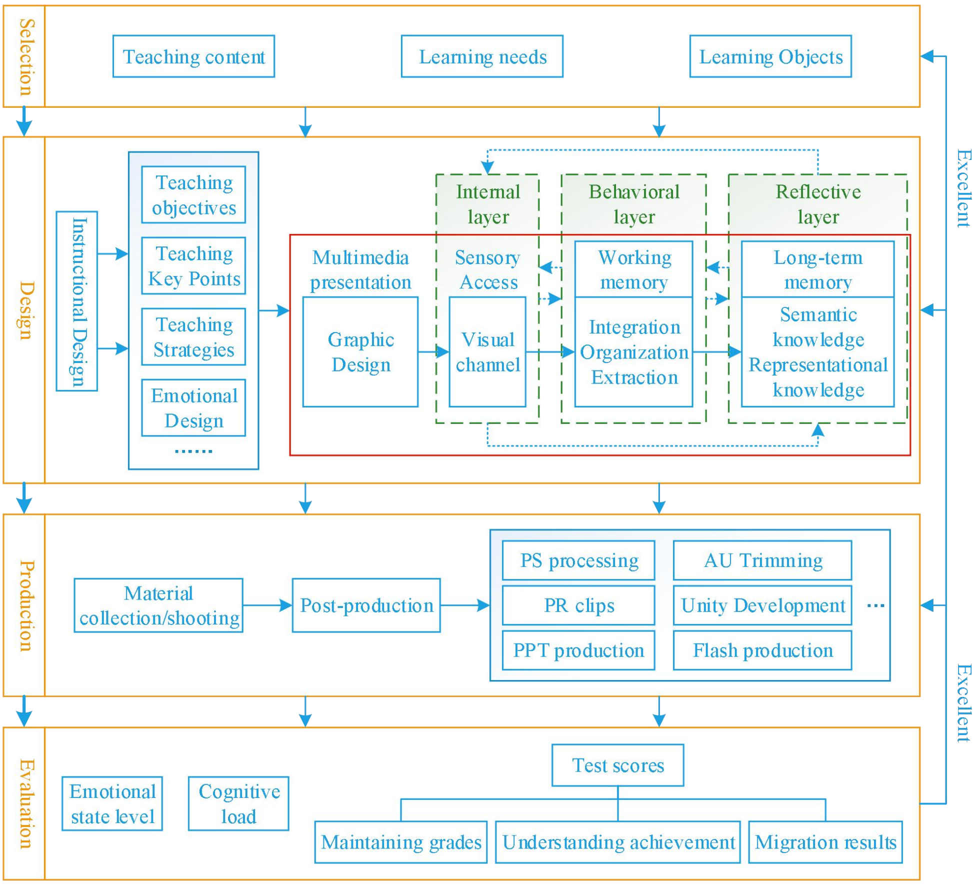

Figure 2. Online teaching resource development model.

(1) Selection of topics: Selection of topics plays an important role in guiding the development of online teaching resources. Selection of teaching activities need to help understand and create an environment for teaching content, according to the characteristics of the learning object feasibility and demand analysis, so as to determine the content of the selected topic.

(2) Design: teaching design is the key link, but also the most direct and concrete expression of teaching ideas. Emotional design and instructional design is a kind of relationship, it has the essential characteristics of instructional design, but also incorporate emotional factors, so that the teaching resources based on emotional design also has its special characteristics. Through the internal layer, behavioral layer and reflective layer of online teaching resources, the three dimensions of emotional design are applied to the learners' visual channel, working memory and long-term memory to induce positive emotions and enhance the learning effect. Internal layer: the visual channel of the model is the internal layer of emotional design, through the design of visual positive factors for online teaching resources, using colorful and anthropomorphic picture design elements, triggering direct and powerful unconscious and subconscious responses, giving learners pleasing sensory stimulation, so as to make them produce immediate emotional responses to the learning effect. Behavioral layer: When learning

behavior occurs, working memory is used for integrating, organizing and extracting new information, but the capacity of working memory is limited and the storage time is short. Reasonable emotional design of the behavioral layer can reduce the external cognitive load and maintain the interest in learning so as to improve the efficiency of working memory and optimize the learning effect. Reflective layer: the emotional experience of learners in the reflective layer mainly comes from their thinking activities, which need to be reasonably designed.CATLM theory points out that the scientific design of emotion can stimulate learners' positive emotions and promote their long term memory of knowledge at the same time. Long-term memory information mainly comes from the content of information processing in the working memory stage, i.e., the information stored after learners' reflective activities. The goal of teaching is the accumulation of knowledge in the long-term memory of the learners, through the addition of reasonable exercise tests, so that the learners produce active reflection activities to increase their cognitive load, in order to improve the learners' long-term memory and learning efficiency. The activities of the reflective layer are closely related to the internal layer and the emotional design of the behavioral layer.

(3) Production: Based on the completion of topic selection and design, the paper-based teaching resources are transformed into online teaching resources. Due to the diversification of online teaching resources, it is necessary to prepare teaching resources, collect and process different types of materials, and then use various types of software to develop and produce them.

(4) Evaluation: The developed online teaching resources are applied to practical teaching and evaluated. Cognitive load scale, positive affective scale and subject test papers are used to evaluate the cognitive load, emotional state level and learning effect of the learners. The conclusions of the evaluation are used to optimize the selection, design and production steps, so as to develop online learning resources with better learning effects, and the evaluation can be used as a reference basis for verifying the validity of the model.

2.2.2. Model characterization

Based on the emotional design factors and the process of online teaching resources development, this study summarizes that the model is characterized by one center, two references, and three stimuli from three aspects: learners, educators and developers, and resource design.

(1) One Center

The development of online learning resources is often teacher-centered rather than learner-centered, and the purpose of resource development is more inclined to meet the motivational needs of developers rather than the learning needs of learners. One center, i.e. learner-centered, adopts the advanced educational theory CATLM to guide the construction of the model, so that it can guide the development of resources in a more objective and reasonable way. The online learning resources under the guidance of this model are designed from the perspective of learners, centering on learners' emotions, and giving more consideration to the stimulation of learners' emotions and interests, so that learners can become their own managers and actively participate in classroom activities.

(2) Two references

From the educator's point of view, the model will provide educators with a new reference for teaching evaluation. Evaluation is an important and indispensable part of daily teaching, and it is an important means for educators to understand the teaching process and improve the quality of teaching. Based on the online teaching resources development model, by integrating the emotional design into the resource development process, educators can take the ability to stimulate learners' positive emotions as a new evaluation factor, thus providing a new reference basis for teaching evaluation. From the developer's point of view, it can provide a reference basis for resource development. Online teaching resources are becoming more and more diversified in terms of sources and presentation methods, reflecting a new understanding of teaching resources and their structure under the modern teaching concept. Resource developers can make use of different development software for different types of resources, and use the model as a reference for the design of screen elements and interactive behavior.

(3) Triple stimulation

According to the information processing characteristics of the human brain, the emotions that learners can feel can be divided into three dimensions: the internal layer, the behavioral layer and the reflective layer of emotions. These three dimensions often influence and interact with each other. From the perspective of online teaching resources development, the model is based on the characteristics of the learning content, the elements that can trigger positive emotions in the internal layer, the behavioral layer and the reflective layer of the three dimensions of the scientific and reasonable arrangement, so that it produces triple stimulation in order to play a role in the learner's emotional experience and further affect the learning effect.

3. ALS-based collaborative filtering recommendation algorithm for Civics teaching resources

3.1. Collaborative Filtering Recommendation Algorithm

3.1.1. The Idea of Recommendation Algorithms

Currently, collaborative filtering algorithms have become one of the most popular among many recommendation algorithms. Admittedly, finding resources in a system that truly fulfill the needs of the user is still a long process, and this technique, too, has been discussed for a long time in the academic world. Nowadays, collaborative filtering recommendation algorithms have become really effective and very sought after algorithms for recommending resources. Typically, and more formally, given a dataset of user actions also known as a user's itemset, we will recommend items to the current user. Inferring the preferences of the target user through the information and preferences of the users associated with the target user is the main idea of collaborative filtering recommendation algorithms. Collaborative filtering methods take as unique input a matrix of user item ratings, a certain item that indicates the current user's likes and dislikes by numerical prediction and a list that includes N recommended items as output [26]. The main implementation of collaborative filtering is to rank the resources that a user may favor according to their similarity and then recommend the top, i.e., the most similar, to the user. Collaborative filtering methods take a given matrix of user item ratings as the only input and typically produce the following types of output: a numerical prediction indicating that the current user will like or dislike an item and a list of recommended items. Such a Top-N table should not contain items that have already been rated by the current user.

3.1.2. Principles of collaborative filtering recommendation algorithms

We need to measure the similarity of items in the clustering process and the similarity of searching for nearest neighbor items, as an example of calculating the similarity of items, by selecting a common score user or other user preference matrix, and then calculating a similar common score vector. Two commonly used similarity calculation formulas are as follows: the Pearson correlation coefficient, and the cosine similarity.

(1) Pearson correlation coefficient

Pearson coefficient is a similarity calculation method based on correlation coefficient. It needs to find the common score of the users to make the accurate calculation result. The U is the set of users who rated item i and item j. The Pearson correlation coefficient formula is as follows (1):

$$sim(i,j)=\frac{\sum_{u\in U}\left(R_{u,i}-\overline{R}_i\right)\left(R_{u,i}-\overline{R}_i\right)}{\sqrt{\left(\sum_{u\in U}R_{u,i}-\overline{R}_i\right)^2}\sqrt{\left(\sum_{u\in U}R_{u,i}-\overline{R}_i\right)^2}} \tag{1}$$

where R_{ui} is the rating of user i for item j and R_i is the rating of item set U for the same item.

(2) Cosine similarity

Item i, item j, as two n-dimensional vectors, the similarity of two items is calculated by taking the angle between the two vectors. For the scoring matrix of $m\times n$, the items and items are computed as similarity as shown below:

$$sim(i,j)=\cos(\overline{i},\overline{j})\frac{\overline{i}\cdot\overline{j}}{|\overline{i}|\cdot|\overline{j}|} \tag{2}$$

(3) Corrective cosine similarity

In the system due to the different preferences and needs of the users, they are very different in scoring the items, which may fluctuate and differ a lot, so the corrective cosine was introduced [27]. The meaning of this formula is to find out the average score of the user's scoring, in accordance with the method of finding the cosine similarity in equation (2). Possible problems are avoided and risks are minimized. The following corrected cosine formula

$$sim(i,i)=\frac{\sum_{u\in U}\left(R_{u,i}-\overline{R}_i\right)\left(R_{u,i}-\overline{R}_i\right)}{\sqrt{\left(\sum_{u\in U}R_{u,i}-\overline{R}_i\right)^2}\sqrt{\left(\sum_{u\in U}R_{u,i}-\overline{R}_i\right)^2}} \tag{3}$$

R with a horizontal line above in the formula refers to the mean score of the scores given to the items by user U.

The implementation of ALS-based collaborative filtering recommendation system for Civics teaching resources relies on behaviors such as user ratings, and if the number of users is very large, there will be the problem of overloading the information of user behaviors, and at the same time, the rating matrix is sparse, and the recommendation speed encounters bottlenecks, which are also the conditions often encountered by collaborative recommendation systems. Therefore it is a good idea to use clustering methods to divide the population into a number of broad categories and then use ALS-based collaborative filtering algorithms for recommending Civics teaching resources in this divided cluster at the time of recommendation. Therefore, in order to solve the problems of sparse simultaneous scoring matrix and bottleneck in the speed of recommendation, and to realize personalized recommendation, this project intends to introduce a hybrid algorithm based on the combination of clustering algorithm and collaborative filtering algorithm to solve the problems in recommendation, increase the efficiency of recommendation, increase the quality of recommendation, and on the basis of the establishment of a more effective recommendation algorithm.

$$sim(u_1,u_2) = 1 - \frac{\sqrt{\sum_{u\in U}\left(r_{u_1,i} - r_{u_2,i}\right)^2}}{commonItems} \tag{4}$$

Equation (4) is the formula used in the definition of Euclidean distance for similarity to be measured. In the formula, the numerator part $d = \sqrt{\sum_{u\in U}\left(r_{u_1,i} - r_{u_2,i}\right)^2}$ is called the Euclidean Distance, and in the case of our study the Euclidean Distance is computed on the principle of for two different users scoring the same item subtract and then quadratic, then sum the squared values and then square. In fact, we can realize from the principle that this process is also the process of calculating the distance between two users. In order to make the results of the calculation of the Euclidean distance is conducive to our use in real situations, this one value and the relationship between similarity needs to change, should be between 0 and 1 value is more appropriate, so that the situation in our formula (4).

Producing the items we recommend: in the 3 steps of the collaborative filtering algorithm for ALS-based Civic Teaching Resources, the third step is very important and is directly related to the results of our recommendation. The final recommendation to the user is the one that is at the top of our ranking. Then how this ranking is obtained. This is mainly based on the second step in which we get the similarity matrix, and in our recommender system, there will be a predictive rating for each item. In this way, those with larger predicted ratings are ranked higher in the list, as explained in detail in formulas (5) and (6).

$$pred(u,i) = \frac{\sum_{i\in ratedItems(u)}\left(sim(u,v) * r_{u,i}\right)}{\sum_{i\in ratedItems(u)} sim(u,v)} \tag{5}$$

$$pred(u,i) = \overline{r}_u + \frac{\sum_{b\in N}\left(sim(u,v) * \left(r_{v,i} - \overline{r}_v\right)\right)}{\sum_{b\in N} sim(u,v)} \tag{6}$$

3.2. Principles of ALS Collaborative Filtering Recommendation Algorithm

The basic principle of the ALS algorithm: If R is a matrix normalized to $\left(R = \left(R^{m\times n}\right)\right) \in \{0,1\}^{m\times n}$, this matrix shows that there are m users and n ratings. The algorithm needs to find a low-rank matrix X to approximate the matrix R and minimize the following objective function:

$$L(x) = \sum_{ij}\left(R_{ij} - X_{ij}\right)^2 \tag{7}$$

In equation (7), the squared error term is $\left(R_{ij} - X_{ij}\right)^2$. Then think about how to solve the optimization problem $\operatorname{argmin}_x L(x)$ efficiently. The matrix decomposition model is shown in Figure 3.

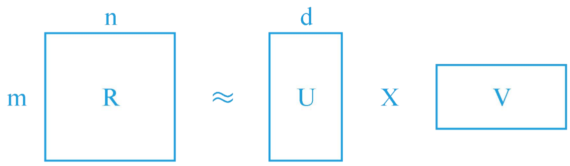

Figure 3. Matrix factorization model.

Regarding the matrix decomposition model $X = UV^T$, where d shows the number of features and r shows the rank of the matrix R, in general $d \ll r, r \approx \min(m,n)$. At this point equation (7) can be rewritten as:

$$L(U,V) = \sum_{ij}\left(R_{ij} - U_{i.}V_{j.}^T\right)^2 \tag{8}$$

After adding a second-order regularization term to Eq. (8), which can prevent overfitting, Eq. (8) can be rewritten as:

$$L(U,V) = \sum_{ij}\left(R_{ij} - U_{i.}V_{j.}^T\right)^2 + \lambda\left\|U_{i.}\right\|\frac{2}{2} + \lambda\left\|V_{j.}\right\|^2 \tag{9}$$

If V is known, one can apply Ridge Regression to infer each row of U, and vice versa. Thus, fixing the V matrix and solving for U_i yields the following formula for solving U_i:

$$U_{i.} = R_{i.}V_{ui}\left(V_{ui}^T V_{ui} + \lambda n_{ui} I\right)^{-1} i \in [1-m] \tag{10}$$

The $R_{i.}$ in Eq. (10) shows the vector of ratings that user i has rated, and V_{ui} shows the feature matrix consisting of the eigenvectors with the eigenvectors that user i has rated. n_{ui} shows how much user i has rated.

Similarly, fixing the U matrix, one can obtain the following formula for solving $V_{j.}$ of the formula:

$$V_{j.} = R_{.j}U_{mj}\left(U_{mj}^T U_{mj} + \lambda n_{mj} I\right)^{-1} j \in [1-n] \tag{11}$$

The $R_{.j}$ in Eq. (11) shows the vector of ratings of the users who have rated item j, U_{mj} shows the eigenmatrix consisting of the eigenvectors of the users who have rated movie j, n_{mj} shows the number of users who have rated item j long ago, and I in Eqs. (10) and (11) shows a unit matrix of $d \times d$.

3.3. Recommendation Algorithm Process

In this paper ALS algorithm is implemented in eclipse with integrated Spark platform and the flow of optimized ALS algorithm is shown in Fig. 4.

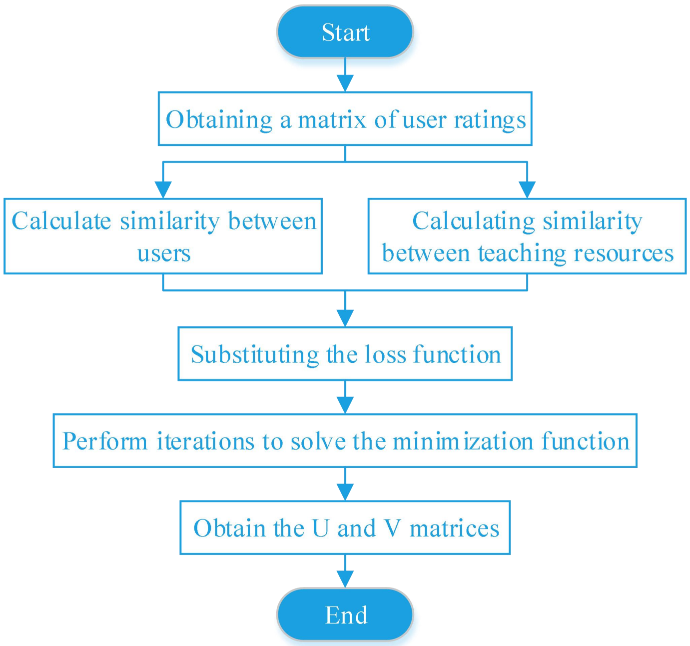

Figure 4. Optimize the ALS algorithm process.

In Step 1, firstly, the user's rating matrix is obtained after the raw data of user ratings, and the similarity between users and users, and teaching resources and teaching resources is calculated. In this paper, we apply the vector cosine method, also called VSS (spatial similarity method), where $N(m)$ shows the collection of teaching resources that user m has, that is, user m has had a promotion of teaching resources, and $N(n)$ shows the collection of items that user n has, and the similarity formula between users m and n is:

$$PC(m,n) = \frac{|N(m) \cap N(n)|}{\sqrt{|N(m)||N(n)|}} \tag{12}$$

The same principle can be known that the similarity formula between teaching resource i and teaching resource j is:

$$PC(i,j) = \frac{|N(i) \cap N(j)|}{\sqrt{|N(i)||N(j)|}} \tag{13}$$

In step 2, a loss function is designed to add the similarity data obtained from the above calculations to the function of Eq. (14).

$$\begin{aligned} f(U,V) = {} & \sum_{(i,j)\in I} \left(r_{ij} - u_i^T g_j\right)^2 + \sum_{i\in I_j} \left(u_{ki} - \frac{\sum_{p\in K(u_i)} PC(m,n) u_{kp}}{\sum_{u_p \in K(u_i)} PC(m,n)} \right)^2 \\ & + \sum_{j\in I_i} \left(g_{kj} - \frac{\sum_{g_q \in K(g_j)} PC(i,j) g_{kq}}{\sum_{g_q\in K} PC\left(g_j\right)} \right)^2 + \lambda \left(\sum_i n_{u_i} \|u_i\|^2 + \sum_j n_{g_j} \|g_j\|^2 \right) \end{aligned} \tag{14}$$

In the above equation, $(i,j) \in I$ shows all user-teaching resource pairs, I_j shows the set of users, I_i shows the set of teaching resources, $K\left(u_i\right)$ shows the N nearest neighbors of user U_i's N nearest neighbors, K shows one random attribute, $K\left(g_j\right)$ shows the N nearest neighbors of the teaching resource g_j, $P(i,j)$ shows the similarity between the teaching resource and the teaching resource,

$P(m,n)$ shows the similarity between users and users [28].

In step 3, the iterative solution of the minimization function is performed in the function of step 2, and finally the U and V matrices are obtained.

Solve U and V exactly by fixing U for V and fixing V for U, using ALS iterative solution as follows:

$$\frac{1}{2} - \frac{\partial f}{\partial u_{ki}} = 0, \quad \forall i,k$$

$$\Rightarrow \sum_{j \in I_i} \left(u_i^T g_j - r_{ij} \right) g_{kj} + \left(u_{ki} - \frac{\sum_{u_p \in K(u_i)} P(m,n) u_{kp}}{\sum_{u_p \in K(u_i)} P(m,n)} \right) + \lambda n_{u_i} u_{ki} = 0, \quad \forall i,k$$

$$\Rightarrow \sum_{j \in I_i} g_{kj} g_j^T u_i + \left(\lambda n_{ui} + 1 \right) u_{ki} = \sum_{j \in I_i} g_{kj} r_{ij} + \frac{\sum_{u_p \in K(u_i)} P(m,n) u_{kp}}{\sum_{u_p \in K(u_i)} P(m,n)}, \quad \forall i,k \qquad (15)$$

$$\Rightarrow \left(M_{I_i} M_{I_i}^T + \left(\lambda n_{u_i} + 1 \right) E \right) u_i = M_{I_i} R^T \left(i, I_i \right) + \frac{\sum_{u_p \in K(u_i)} P(m,n) u_p}{\sum_{u_p \in K(u_i)} P(m,n)}, \quad \forall i$$

$$\Rightarrow u_i = A_i'^{-1} V_i', \quad \forall i$$

The above equation (15) is solved for u_j at each iteration, and similarly, with respect to g_j, there is:

$$g_j = \left(U_{I_i} U_{I_i}^T + \left(\lambda n_{g_j} + 1 \right) E \right)^{-1} \left[V_I, R^T \left(j, I_J \right) + \frac{\sum_{g_q \in K(g_j)} P(i,j) g_q}{\sum_{g_q \in K(g_j)} P(i,j)} \right], \quad \forall j \qquad (16)$$

3.4. Testing and analyzing the recommendation system

3.4.1. Analysis of experimental results on the overall recommendation quality of the system

In the comparison experiment, the experimental data and conditions are kept unchanged, and the three groups of systems based on the content recommendation model (control experimental system I), based on the collaborative filtering recommendation model (control system II), and the model in this paper are subjected to multiple rounds of repetitive experimental tests, and the experimental results of the average absolute error are shown in Table 1. The experimental results of the comprehensive evaluation index F value of the system are shown in Table 2. The experimental results show that the MAE of the recommendation system of multimedia teaching resources for Civic and political education using the method of this paper is significantly lower than that of the control experimental systems I and II, and its average value is only 0.885. This indicates that the recommendation results of the method of this paper have small errors and the recommendation algorithm is accurate. The F-value of the recommendation system proposed in this paper is significantly higher than that of the control experimental systems I and II, which indicates that the experimental method is effective. This shows that the method of this paper improves the overall quality of the recommendation system.

Table 1. Experimental results of average absolute error.

	1	2	3	4	5	6
Ours	0.93	0.90	0.85	0.90	0.87	0.86
Control system I	1.09	1.22	1.11	1.10	1.08	1.10
Control system II	1.12	1.18	1.16	1.18	1.13	1.14

Table 2. The experimental results of the comprehensive evaluation index F value.

	1	2	3	4	5	6
Ours	85.88	86.55	87.02	88.10	84.87	84.27
Control system 1	82.19	81.79	81.45	82.72	82.59	83.13
Control system 2	78.16	79.63	79.17	78.63	78.29	77.82

3.4.2. Analysis of experimental results on the quality of new user recommendations

Comparison of experimental data and conditions remain unchanged in the experiment, using the experimental design of the three groups of experimental systems for multiple repetitions of experimental tests, it can be found that the recommended system based on the method of this paper after the addition of a new user, the recommended system of the lower value of the comprehensive evaluation indexes can still be kept stable, which also indicates that the method of this paper's Civic and Political Education multimedia teaching resources recommended model can solve the recommended system of the user's cold start problem. This also shows that the recommendation model of multimedia teaching resources for Civic and Political Education using the method of this paper can solve the user cold start problem of recommendation system.

3.4.3. Analysis of experimental results on system stability

The recommended MAE value of the system real-time is shown in Table 3, the MAE value of the recommended system in this paper decreases, and the system algorithm accuracy improves, as the experimental time grows, the MAE value of the algorithm decreases, and the MAE of the accuracy does not continue to change after the 15th day, and the MAE value of its MAE value is 0.82, and at this time, the algorithm efficiency converges.

Table 3. The system recommends MAE values in real time.

	1	5	10	12	15	18	20	25
Ours	0.92	0.89	0.85	0.86	0.82	0.82	0.82	0.82
Control system 1	1.15	1.22	1.21	1.10	1.07	1.11	1.11	1.29
Control system 2	1.11	1.22	1.46	1.17	1.12	1.27	1.22	1.23

4. Empirical studies

4.1. Study design

In order to test the effectiveness of multimedia teaching resources for Civic Education based on Artificial Intelligence in teaching practice, this paper analyzes the teaching effectiveness by using SPSS tool. The steps of empirical analysis are described below.

4.1.1. Experimental Objects

Classes of the same grade in a teacher training college specializing in Civic and Political Education were selected as the experimental group and the control group (Class 1 and Class 2) to carry out the Civic and Political Education course, and were taught by the same teacher adopting different teaching methods. With other conditions remaining basically the same, the questionnaire of the experimental classes was used as a variable for difference analysis, so as to verify whether there is a significant difference between the Civics competence obtained by teaching Civics education multimedia teaching resources based on Artificial Intelligence and that obtained by adopting conventional teaching methods.

4.1.2. Analytical methods and processes

The author examined the data results using the independent samples t-test, which is more commonly used in the statistical practice of evaluating the effectiveness of teaching and learning, to determine the probability of the difference between the two occurring through the theory of t-distribution to determine whether the difference between the two averages is significant or not. This method is more convincing than simply using the mean, median and other values between two samples to determine the difference between them.

4.2. Statistical results

4.2.1. Analysis of the level of students' political thinking ability in the two classes before the experiment

Before conducting the teaching experiment the Civics competence of the two classes was tested according to the Skills Evaluation Scale, and the scores of the scales were entered into the SPSS software for the analysis and comparison of the data. Through the scientific and educational analysis of SPSS software, the significance level of P-value > 0.05, which means that there is no significant difference between the Civics competence of students in these two Civics classes. That is to say, the level of Civics competence of the control class and the experimental class is roughly equal.

4.2.2. Analysis of the level of students' political thinking ability in the two classes after the experiment

In order to compare the level of Civics competence between the control class and the experimental class, and to examine whether there is any difference in the performance of the two classes after the corresponding Civics competence training. The subject group adopts independent samples T-test. The independent samples T-test statistics are shown in Table 4, where the different scores of Civic and Political Competence of the two groups of data are compared, and the experimental class is significantly higher than the control class, which shows that the method of this paper has a significant impact on the improvement of the Civic and Political Competence of the students of teacher training class of the Civic and Political Education program.

Table 4. Independent sample t-test statistics.

	Class	N	Mean value	Standard deviation	The standard error of the mean
Blackboard writing and drawing	1	55	15.25	1.513	0.197
	2	55	14.65	1.48	0.171
Oral expression	1	55	17.12	1.11	0.178
	2	55	13.25	0.875	0.14
Organize teaching skills.	1	55	16.82	1.136	0.128
	2	55	13.43	1.067	0.142
Import skills	1	55	17.19	1.053	0.111
	2	55	13.39	1.098	0.13
Demonstration skills	1	55	16.85	1.082	0.105
	2	55	13.49	1.201	0.13
Explanation skills	1	55	17.21	1.122	0.145
	2	55	13.5	1.092	0.137
Questioning skills	1	55	16.93	1.108	0.144
	2	55	13.55	0.927	0.128
Feedback reinforcement skills	1	55	16.89	0.984	0.148
	2	55	13.52	1.111	0.159
End Skill	1	55	17.05	1.045	0.127
	2	55	13.01	0.987	0.105
Comprehensive teaching skills	1	55	17.35	0.974	0.157
	2	55	12.78	0.895	0.127

The results of the independent samples T-test analysis of the board board drawing are shown in Table 5, respectively. The two groups of data are independent of each other, not related to each other two groups of samples from the overall show a normal distribution, variance chi-square, two groups of variance is equal, in line with the conditions of the independent samples t-test.SPSS automatically based on the one-way analysis of variance to calculate the F statistic and the probability of the value of P. SPSS will automatically two groups of samples of the mean, the number of samples, the variance of the sampling distribution of variance to bring into the formula for the formula of the variance, to obtain the t statistic of the observation value and the corresponding probability P-value. The Levene statistic in the board book board drawing skill is 0.179 and the significance p-value is 0.682 > 0.05, so its variance is chi-square. The independent samples t-test statistic between different groups is 1.877 and the p-value is 0.066>0.01 for board board drawing, so the difference between the experimental and control classes in board drawing skills is not significant. It can be seen that the method of this paper did not have an effect on the students' board book board drawing skills.

Table 5. Independent sample t test analysis of blackboard painting.

							T-test of the mean equation			
		Levene test of the variance equation		T-test of the mean equation			Mean difference	Standard error value	95% confidence interval of the difference	
		F	Sig.	t	df	Sig.(Bilateral)			Lower limit	Upper limit
Blackboard writing and drawing	Suppose the variances are equala	0.179	0.682	1.877	121	0.066	0.512	0.293	-0.036	1.082
	Suppose the variances are not equal			1.877	119.856	0.066	0.512	0.293	-0.036	1.082

4.3. Analysis and discussion

4.3.1. Oral Expression and Civics Skills

The mean value of oral expression in the experimental class (class1) was 17.12 respectively, which was significantly higher than the mean value of oral expression in the control class (class2) which was 13.25. The mean value of the scores of the experimental class (class1) in Civic and political ability is 16.82, which is significantly larger than the mean value of the scores of Civic and political ability of the control class (class2) which is 13.43, which shows that the method of this paper has a significant effect on the students' oral expression and Civic and political ability.

The independent samples t-test analysis of oral expression and civic skills is shown in Table 6. The Levene statistic for oral expression skills is 3.956, sig value=0.046, this p-value<0.05, it can be seen that the variance is not uniform. Observation of oral expression skills t=20.869, p-value=0.000<0.01, it is seen that there is a difference in the performance of the experimental class and the control class in the oral expression skills of the two classes after the experiment. The Levene statistic of Civic and Political skills is 0.276, sig value=0.563, this P value>0.05 and the test of chi-square is chi-square. The statistic of independent samples test between different groups is t=17.562, p-value=0.000<0.01, it can be seen that the Civics competence of the experimental class and the control class shows significant differences. The method of this paper has a significant impact on students' oral expression and Civic and Political competence.

Table 6. Independent sample *t*-test.

						T-test of the mean equation			
	Levene test of the variance equation		T-test of the mean equation			Mean difference	Standard error value	95% confidence interval of the difference	
	F	Sig.	t	df	Sig.(Bilate			Low	Upp

						ral)			er limit	er limit
Oral expression	Suppose the variances are equala	3.956	0.046	20.869	116	0	3.869	0.179	3.566	4.215
	Suppose the variances are not equal			20.869	111.562	0	3.869	0.179	3.566	4.215
Organizational teaching skills	Suppose the variances are equala	0.276	0.563	17.562	116	0	3.526	0.209	3.126	3.862
	Suppose the variances are not equal			17.562	119.356	0	3.526	0.209	3.126	3.862

4.3.2. Introductory Skills and Civics Competencies

The mean value of the introduction skills of the experimental class (class1) is 17.19 respectively, which is significantly higher than the mean value of the oral expression of the control class (class2) is 13.39.The mean value of the scores of the ending skills of the experimental class (class1) group is 17.05, which is significantly greater than the mean value of the scores of the Civic and Political competence of the control class (class2) is 13.01.It is clear that the method of this paper has a significant effect on the Civic Teacher's introduction and the Civic and Political competence significantly.

The independent samples t-test analysis of the introduction skill and end skill is shown in Table 7. The results of the test show that the LeveneF value of introduction skills = 0.223 and the significance p-value = 0.653, which is significantly > 0.05, so the variance is chi-square. The independent samples test statistic between the different groups was 18.362 with a p-value of 0.000, which is significantly <0.01, and it can be seen that the performance of the experimental and control classes in the introductory skills showed a significant difference. The LeveneF value for ending skills = 1.503 with a p-value of 0.241 > 0.05, so the test of variance alignment is chi-square. The t-value of the independent samples test statistic for the ending skill is 22.306 and the p-value is 0.000<0.01, so there is a difference between the scores of the experimental class and the control class for the introduction skill, which means that the method of this paper has a significant effect on the students' end-of-introduction skills.

Table 7. Independent sample t-test analysis of importing skills and ending skills.

							T-test of the mean equation			
		Levene test of the variance equation		T-test of the mean equation			Mean difference	Standard error value	95% confidence interval of the difference	
		F	Sig.	t	df	Sig.(Bilateral)			Lower limit	Upper limit
Import	Suppose the	0.223	0.653	18.362	116	0	3.595	0.203	3.296	4.036

skills	variances are equala									
	Suppose the variances are not equal			18.362	117.963	0	3.595	0.203	3.296	4.036
End Skill	Suppose the variances are equala	1.503	0.241	22.306	116	0	4	0.193	3.663	4.296
	Suppose the variances are not equal			22.306	117.421	0	4	0.193	3.663	4.296

4.3.3. Presentation skills and ability to explain Civics

The mean value of presentation skill of the experimental class (class1) is 16.85, which is much larger than the mean value of 13.49 of the control class (class2).The mean value of explaining skill of the experimental class (class1) is 17.21, which is larger than the mean value of 13.5 of the control class (class2), and it is concluded that the method of this paper has had a significant impact on the students' presenting skill and explaining skill.

The independent samples t-test analysis for presentation skills and explaining skills is shown in Table 8. The Levene statistic for Presentation Skills is 0.003 with p-value = 0.973 > 0.05, which shows that it passes the chi-square test. The t=17.012 and p-value=0.000 for the independent samples test is significantly less than 0.01, indicating that there is a difference in presentation skills between the experimental and control classes. The Levene statistic for presentation skills was 0.012 with a p-value of 0.922, which is >0.05 and shows variance alignment. The t-statistic of independent samples t-test between different groups was 18.532 with a p-value = 0.000 < 0.01, which shows that there is a difference in presentation skills between the experimental and control classes. In conclusion, the method of this paper had a significant effect on both presentation skills and explaining skills of the students.

Table 8. Independent sample t-tests for demonstration skills and explanation skills.

									T-test of the mean equation	
		Levene test of the variance equation		T-test of the mean equation			Mean difference	Standard error value	95% confidence interval of the difference	
		F	Sig.	t	df	Sig.(Bilateral)			Lower limit	Upper limit
Demonstration skills	Suppose the variances are equala	0.003	0.973	17.012	116	0	3.6	0.212	3.082	3.912
	Suppose the			17.012	118.365	0	3.6	0.212	3.082	3.912

	variances are not equal									
Explain skills	Suppose the variances are equal	0.012	0.922	18.532	116	0	3.9	0.203	3.309	4.085
	Suppose the variances are not equal			18.532	118.265	0	3.9	0.203	3.309	4.085

4.3.4. Questioning Skills and Feedback Reinforcement Skills

The mean value of the scores of questioning skills in the experimental class (class1) is 16.93 respectively, which is significantly higher than the mean value of 13.55 in the control class (class2).The mean value of the scores of feedback reinforcement skills in the experimental class (class1) is 16.89, which is significantly greater than the mean value of 13.52 in the control class (class2).It is clear that the method of this paper has the following effects on the questioning skills of the students and feedback reinforcement of the civic and political skills influence is obvious.

The independent samples t-test for questioning skills and feedback reinforcement skills is shown in Table 9. The observed value of the F statistic of the test is 0.015, and the corresponding P value is 0.926. The significance level is 0.05, and it is obvious that the P value is >0.05, which shows that there is no significant difference in the overall variance of the two classes, and the null hypothesis should be rejected if the significance level is 0.05, and the probability P value, which is that there is a significant difference in the means of experimental and control classes. t statistic has an observed value of 18.765, and the corresponding two-tailed probability P-value for the 95% confidence interval for the difference between the overall means of the two classes in the table does not cross 0, which proves in another way that the methodology of this paper has a significant impact on the questioning skills and feedback reinforcement skills of the students.

Table 9. Independent sample t-tests for questioning skills and feedback skills.

							T-test of the mean equation			
		Levene test of the variance equation		T-test of the mean equation			Mean difference	Standard error value	95% confidence interval of the difference	
		F	Sig.	t	df	Sig.(Bilateral)			Lower limit	Upper limit
Questioning skills	Suppose the variances are equala	0.015	0.926	18.765	116	0	3.526	0.185	3.149	3.85
	Suppose the variances are not			18.765	115.652	0	3.526	0.185	3.149	3.85

	equal									
Feedback reinforcement skills	Suppose the variances are equala	1.426	0.243	18.365	116	0	3.526	0.196	3.132	3.892
	Suppose the variances are not equal			18.365	115.895	0	3.526	0.196	3.132	3.892

4.3.5. Comparison of Mean Teaching Composite Skills

The mean value of comprehensive skills of teaching in the experimental class (class1) is 17.35, which is much higher than the mean value of 12.78 in the control class (class2), and it is concluded from the test that the methodology of this paper has a significant impact on the comprehensive skills of teaching of the students.

The results of the independent samples t-test for teaching composite skills are shown in Table 10.The observed value of the F-statistic is 1.895, which corresponds to a p-value of 0.169. The level of significance is 0.05 and it is clear that the p-value > 0.05 shows that there is no significant difference in the overall variance of the Civic Aptitude scores of the two classes. In the second step, the test of the overall mean of the combined teaching skills of the two classes was carried out, looking at the results of the t-test in the first column since there was no significant difference in the overall variance of the two classes. In this case, the observed value of the t-statistic is 25.963 and the p-value is 0.000<0.05, which shows that the null hypothesis should be rejected, i.e., there is a significant difference between the means of the experimental and control classes. The 95% confidence interval for the difference in the overall means of the two classes in the table does not cross 0, which proves from another point of view that the methodology of this paper has a significant impact on the students' teaching and learning integration skills.

Table 10. The independent sample t-test results of comprehensive teaching skills.

							T-test of the mean equation			
		Levene test of the variance equation		T-test of the mean equation			Mean difference	Standard error value	95% confidence interval of the difference	
		F	Sig.	t	df	Sig.(Bilateral)			Lower limit	Upper limit
Comprehensive teaching skills	Suppose the variances are equala	1.895	0.169	25.963	116	0	4.426	0.168	4.265	4.839
	Suppose the variances are not equal			25.963	115.659	0	4.426	0.168	4.265	4.839

5. Conclusion

In this paper, based on CATLM theory, combined with ALS recommendation algorithm, we construct a multimedia teaching resources development and recommendation model for Civic and Political Education. The model improves learning efficiency by helping users accurately find the resources they need. The conclusions drawn from the article are as follows:

(1) In the average absolute error experiment, the MAE value using this paper's method is significantly lower than that of the control experimental system I (based on the content recommendation model) and the control system II (based on the collaborative filtering recommendation model), which indicates that the recommendation result of this paper's method has a small error and the recommendation algorithm is accurate, and its mean value is 0.885.

(2) The mean value of teaching comprehensive skills of the experimental class is 17.35, which is higher than that of the control class of 4.57, which shows that teaching with the method of this paper has a significant impact on students' teaching comprehensive skills.

In summary, the multimedia teaching resources development model of Civics education constructed in this paper has a significant impact on students' Civics skills, and the research results of this paper will provide a good reference and basis for the design and development of online teaching resources.

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