Innovation of History Teaching Mode Based on Digital Technology

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ABSTRACT

With the continuous progress of science and technology, the trend of integrating science and technology into education has been unstoppable, and educators are constantly striving to find a perfect teaching method to serve education. In this article, the innovative research on the teaching mode of history course based on digital technology is carried out. This article puts forward the design of digital resources of history curriculum, and on this basis, designs and implements the algorithm of recommending history curriculum resources. Firstly, CF (collaborative filtering) algorithm based on users is implemented to find similar neighbors for users, and if there are no similar neighbors, it is calculated according to content recommendation. Secondly, the user's ability scoring model not only contains the basic attributes of users, but also involves the ability scoring of course training users, and the calculation of ability comes from the calculation of text mining.

KEYWORDS

Course recommendation, Digital teaching, History course

INTRODUCTION

Teaching is a two-way activity, which needs to give full play to the enthusiasm and initiative of both teachers and students. In the traditional "full hall irrigation" teaching method, students' learning is passive, and teachers' teaching is also passive (Li,2021). This teaching phenomenon is still widespread, despite not being conducive to the cultivation of students' innovative thinking (Li, 2021). The trend of integrating science and technology into education is pervasive, as educators are constantly striving to find a perfect teaching method to serve education. History is a comprehensive social science, and for history teachers, relying on traditional teaching resources is ineffective and makes it difficult for students to obtain extensive historical knowledge. Relying on any one approach to resources will limit students' learning. The study of history requires exposing students to the remarkable features of the past. If historical figures and events cannot be presented clearly to learners, they will struggle to perceive and understand history. Therefore, multiple methods of presenting historical materials are needed to create effective learning situations.

Traditional history teaching pays attention to the teaching of historical knowledge, sorting out the sequence and cause and effect of historical events; this often leads to the phenomenon of "cramming" in a step-by-step and passive receptive learning mode (Nan, 2019). Most students trained by this

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teaching mode have not acquired the ability to solve historical problems, let alone develop a spirit of questioning and innovation. Therefore, it is necessary to improve teaching methods and means and establish innovative classroom teaching models (Chen & Zheng, 2020).

The teacher-student interaction mode needs to be reformed by changing the phenomenon of students' passive acceptance of learning and teacher-centered delivery of information (Shen, 2021). An improved method of interaction would consider differences in teaching, respect students and their opinions, and promote students' independent learning and thinking. In view of this, exploring a practical teaching mode and giving full consideration to the effectiveness of history classroom teaching has become an important research topic. With the continuous development and changes of society, new knowledge, skills, and quality requirements are constantly emerging. The education system needs to adapt to these changes in order to cultivate talents who meet the needs of modern society. Based on the requirements of the new curriculum reform and the practice of history teaching, it is recommended that in teaching history, instructors should choose the most suitable classroom teaching method according to educational objectives, teaching contents, and students' characteristics, so as to improve the quality of classroom instruction(Yin, 2019).

This paper describes innovative research on the mode of teaching history courses with digital technology. This paper presents the design of digital resources for history courses, and it analyzes the learners' grasp of basic knowledge and skills, learning habits and patterns, and the key contents of training courses and teaching purposes. On this basis, a history course resource recommendation algorithm is designed and implemented.

RELATED WORK

In the 21st century, the popularization of the internet and the rapid development of modern network technology changed virtually all aspects of society in a revolutionary manner. One area, in particular, that has benefitted from advances in technology is the field of education. Compared with traditional education methods, online education has obvious advantages, such as open learning systems, the sharing of educational resources, the diversity of teaching strategies, and the flexibility of learning methods (Jian, 2019a; Chowdhury et al., 2022). Brasher et al. (2022) support more effective teaching and learning by establishing a new generation of online courseware and improving the attractiveness of teaching content itself. Zaikov et al. (2021) proposed the concept of "personalized teaching", which involves using different teaching strategies and methods to impart the same knowledge, and defined 9 sorting rules applied to learning list design. Lin (2021) studied open courseware and discussed the significance of open courseware for global online education. Dama et al. (2021) analyzed from the perspective of economics that open educational resources can bring disruptive innovation in the field of improving teaching, but the open educational resources cannot replace the contribution of traditional school education to the economy.

The new teaching mode mainly focuses on online courses. Online courses have unique characteristics and applicable scenarios, such as the diversity of content forms(Yu et al., 2021). This characteristic makes it difficult to recommend online courses. Generally, only text information such as course titles, introductions, and classifications can be used, or video content can be manually labeled(Zhao et al., 2022). Alsaadi et al. (2022) proposed an online course recommendation system based on topic model. Their research states that topic model is a common model in text mining, and it has been proved in experiments and applications, based on its advantages in accuracy and efficiency.

RESEARCH METHOD

Design of Digital Resources for History Courses

History is a concentrated reflection on the evolution of society, linking the past, present, and future. The traditional teaching method of history class is relatively rough, because the entire grade uses a set of teaching ideas or even a set of courseware(Lin, 2021). The whole grade uses a set of teaching ideas or even a set of courseware. In the teaching mode of digital classroom, after students have finished their autonomous learning, instruction is targeted and takes into account the specific situation of students. This new teaching mode can help students clarify the logic of a lesson and also aid in filling in the gaps in their learning.

Most students and even some subject teachers think that one can earn high marks on an exam only by reciting information. Of course, many questions in traditional history exams test students' memory of facts. But in today's society, schools and employers have increasingly high requirements for students' comprehensive abilities. The digital classroom mode of teaching history combines students' individual learning, online learning, and group inquiry activities. Students learn about basic historical events through independent learning, sort out historical clues, and then ask questions, which exercises students' thinking and questioning abilities and is conducive to the cultivation of students' innovative spirit. Through digital technology, history teachers can carry out exploratory learning and practical exploration on the key points, clarify passages in history textbooks as needed, cultivate students' ability to acquire historical knowledge, and establish correct historical understanding.

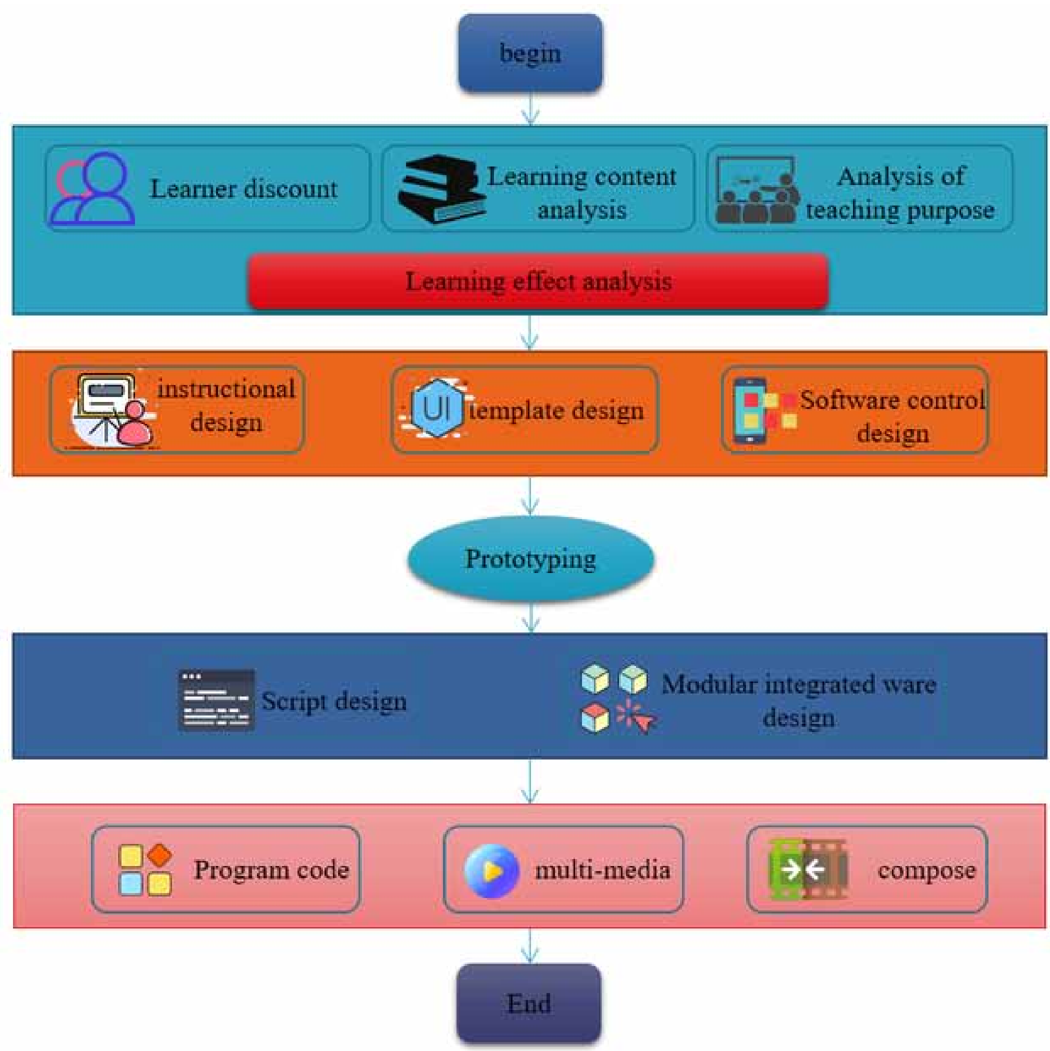
With the rapid development of information technology and the comprehensive promotion of educational informatization, the term "digital teaching resources" has been widely used, but without a clear and generally accepted understanding of its meaning. Digital teaching resources refer to the sum of all information resources that can serve teaching activities and can be spread and presented on computers or computer networks after digital processing, including the digitalization of people, money, and things(Dama, 2021). Digital teaching resources can be defined and described from the following aspects: their characteristics, types, applicable conditions, technical implementation methods, and presentation methods. There are many similar concepts to digital teaching resources. This study holds that digital teaching resources are all human and non-human resources that can be used by teachers or learners in the process of supporting digital teaching. A digital teaching resource database is a shared and open resource platform that is established according to the inherent logical relationship of the course and the corresponding technical specifications and standards; it can be used by teachers and learners to complete the digital teaching process.

Curriculum integrated resources refer to digital teaching materials used for education and training, typically including text, multimedia, interactive elements, and evaluation tools, which can be used alone or in combination with other resources to support teaching and learning activities. These resources are designed to help teachers and students better understand and master specific themes or course content. The development process of curriculum integrable ware resources is shown in Figure 1. Each knowledge point of integrable ware should have a clear teaching goal, ranging from a simple goal to a more comprehensive goal according to the aggregation degree of learning content; the developed integrable ware resources are divided and combined at multiple levels according to the course learning goal. According to the development time and development cost, the granularity of resources is determined, with the understanding that if granularity is too large, information loss will likely result. If the granularity is too small, the cost of manpower and time are likely to increase when tagging the metadata of integrable ware resources, with simultaneous bandwidth problems occurring during the uploading of resources to the online learning platform.

In the demand analysis, learners' mastery of the necessary basic knowledge and skills, learning habits and learning patterns, key contents of the training course, and the teaching purpose are considered. The next steps are teaching oriented and emphasize the nature and objectives of the course. The specific method includes breaking down the content into learning modules, and then creating a course outline and content organization structure. Through customer verification mode, developers can communicate with users as early as possible in the process; obtain customers' guidance, suggestions, and feedback; ensure the quality of integrable ware development; and control risks in time.

The digital teaching resource library mainly serves the teaching of teachers and students, and the rationality of the resource library structure, the practicability of the content, and the scientific design

Figure 1. Process for developing digital resources for a history course



should be taken into account in the construction(Jiang et al., 2021). The design and construction of digital teaching resources according to unified technical standards is conducive to the wide sharing among digital teaching resource banks, avoiding unnecessary waste of manpower, material resources, and financial resources, effectively improving the utilization efficiency of digital teaching resource banks and maximizing their functions and benefits (Guan et al., 2020). The teaching resource library for a history course generally includes the following parts: memorabilia, research summary, reference documents, guide to historical works, image resources, teaching courseware (PPT)(Khadjieva, 2019). Additional teaching resources with the characteristics of the discipline can be designed.

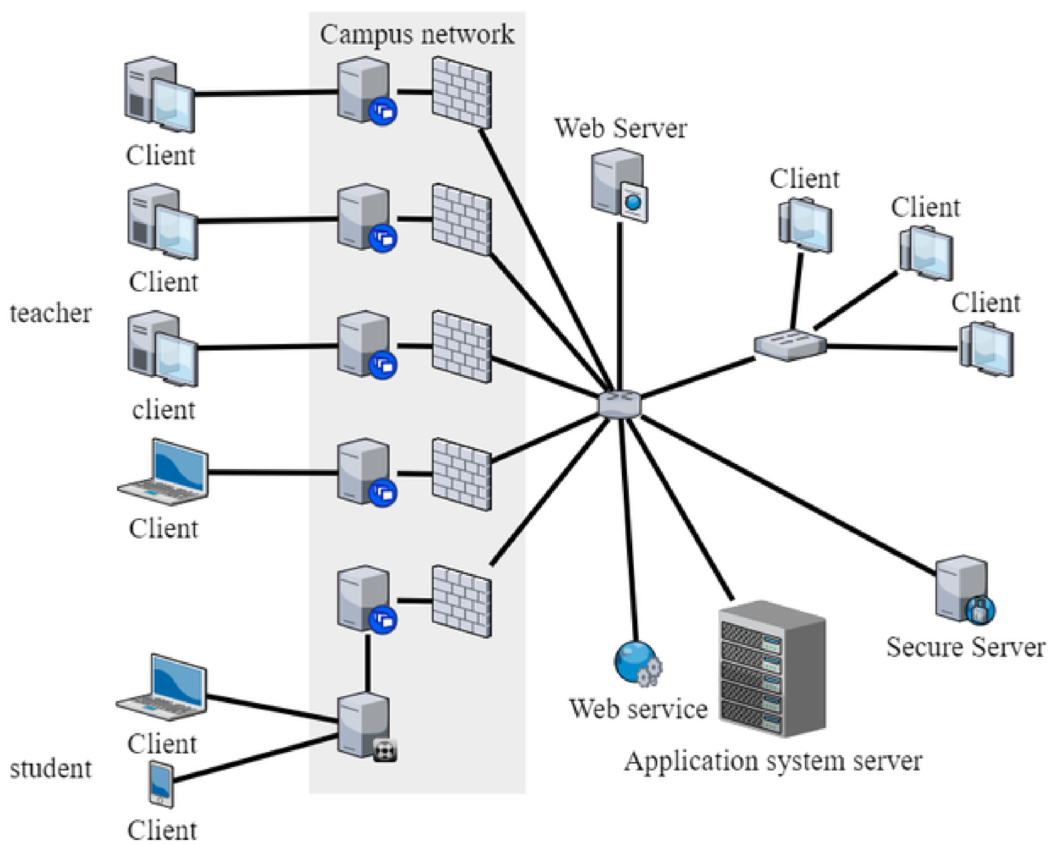
The construction of digital campuses makes the acquisition of educational resources more convenient through intelligent terminal devices. Therefore, the construction and application of a teaching resources platform is particularly important (Ma et al., 2019). The construction of a digital campus must adhere to the principle of "unified planning, step-by-step implementation, strengthening application, integrating resources and sharing data"(Zhao et al., 2022). The information of each department forms an information island, which leads to duplication of work and can adversely affect the information consistency of the institution and inconvenience daily management of resources. Therefore, during the construction of a digital campus, it is necessary to realize data sharing among application systems, ensure data consistency, and truly realize data informatization.

The core application support system and information service system in the construction of a digital campus constitute the system model of a digital campus network. The information portal is the access entry point of the whole digital campus integrated management platform, which provides all information systems and resources to users with a unified interface and provides navigation and information retrieval services for users. Figure 2 shows the overall architecture of integrated information subscribers, which is a solution for large-scale information resource integration for campus network users.

The comprehensive information portal provides customized information resources and business data based on the user's identity to provide personalized services to users. Teaching resources include specialty settings, teaching plans, teaching progress tables, electronic teaching plans, teaching materials, homework, and examination question banks; these are primarily supplied by the academic affairs office and the teaching management departments. Such resources can be gradually established by all teachers in relevant departments using multimedia production centers (Mao, 2022).

The key to maximizing the benefits of digital teaching resources lies in whether teachers can effectively use teaching resources to serve classroom instruction. Therefore, it must be determined if teachers are willing to use digital teaching resources, whether they will use them often, and whether they can use them well. The effective application of high-quality teaching resources can provide

Figure 2. Overall framework of integrated information portal



effective guidance for teachers to carry out curriculum reform and demonstration teaching. The construction of history curriculum is an important carrier of the organic combination of curriculum reform and teaching resources construction. High-quality teaching resources centered on a history curriculum form the basis for an online learning support system that displays relevant resources on the internet for students to use in autonomous learning and online interaction.

Recommended Design of History Curriculum Resources

History education should cultivate people with civic quality, humanistic quality, cognitive ability, distinctive personality and innovative consciousness (Seidel et al., 2020). In order to understand history, students must grasp the overall context of historical developments and form the concept of time and space. In the process of exploring history, individuals form the consciousness of historical evidence and enhance their cognitive ability (Khadjieva, 2019).

With the popularity of online education, users can learn information in any field online, but finding the courses they want can be a significant problem for users (Linda et al., 2019; Das et al., 2019). Under the current classification system, users can find the courses they want quickly, but with the further development of online courses, classification will become more detailed and complex, increasing the difficulty of users to find courses. In addition, users may be uncertain of the category to which their interests belong; thus, classification alone is not a sufficient basis for the development of online courses, nor can it meet the growing needs of users.

A recommendation system is a model built by collecting user data and producing the best recommendation based on an algorithm. At present, the information available includes three elements: the training plan of history majors, students' basic attributes, and students' achievements in taking courses. The generation of a recommendation object model is the process of modeling these contents. The overall architecture of the recommendation system is a "conversion" hybrid recommendation technology. Adjacent neighbors refer to other users who share similar interests or behavior patterns with a specific user in a recommendation system. First, the CF algorithm based on users is implemented to find similar neighbors for users, and if there are no similar neighbors, the recommendation calculation is based on the content. Next, the "user's ability scoring model" is implemented. It includes the basic attributes of users and the grading ability of course training users.

The recommendation system is defined as follows: a function p is defined, and the function value of the function p represents the predicted value of user u interest in item o (Meng et al., 2021). If the item set, user set and recommendation set are respectively represented by O, U, R, and the formal expression of this process is as follows:

$$p : U * O \to R \tag{1}$$

After calculation, the function result is found; that is, the system item set with the largest predicted value of user interest is finally recommended to users. It is represented by the following formula (2):

$$\forall u \in U, o_u = \arg\max p\left(u, o\right), \quad o \in O \tag{2}$$

o corresponds to the representation of the main carrier video resources in the research topic, so the above formula is applied to this paper, and the following formula (3) is expressed:

$$\forall u \in U, v_u = \arg\max p\left(u, v\right), \quad v \in V \tag{3}$$

Among many recommendation algorithms, CF recommendation algorithm is one of the most successful. The basic idea of CF recommendation algorithm draws lessons from people's logical thinking of purchasing goods or services in daily life. The basic principle of CF recommendation technology is that by using the historical evaluation data of the target user, one can find the neighboring users with similar interests to the target user (Jian, 2019b).

Generally, the recommendation result is that the Top-N project with the highest interest of the target user or the Top-N project with the highest prediction score will be formed into a recommendation result set and recommended to the user, as shown in formula (4).

$$p_{u,i} = \bar{R}_i + \frac{\sum_{u_n \in NN_U} sim\left(u, u_n\right) * \left(R_{u_n,i} - \bar{R}_{u_n}\right)}{\sum_{u_n \in NN_U} \left|sim\left(u, n\right)\right|} \tag{4}$$

where $p_{u,i}$ represents the prediction score of the target user u on the recommended object i, NN_U represents the nearest neighbor set of the target user u, $sim\left(u, u_n\right)$ represents the similarity between the target user u and the user u_n, $\bar{R}_i$ represents the average score of the item i, $R_{u_n,i}$ represents the score of the user u_n on the item i, and $\bar{R}_{u_n}$ represents the average score of the items evaluated by the user u_n.

Clustering is an unsupervised statistical algorithm for classification. In the clustering algorithm, the information indicating data classification does not exist. There is no need to mark the data in advance, and the data samples are usually processed according to a certain standard, such as distance (Li & Li, 2019).

Assuming the existing data set $X = \left\{x_1, \cdots, x_n\right\}$, the clustering result obtained by k-means clustering is $C = \left\{c_1, \cdots, c_k\right\}$, and the corresponding target value function is shown in formula (5).

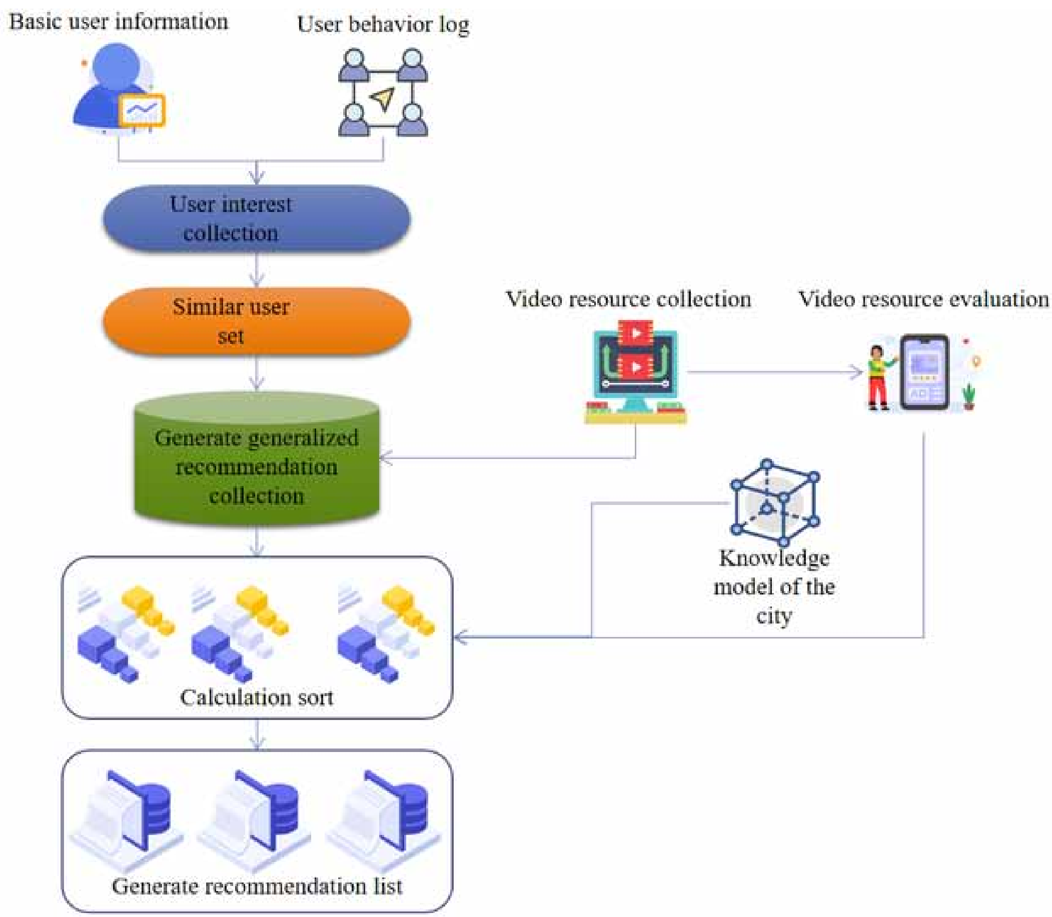
$$E = \sum_{i=1}^{k} \sum_{x \in c_i} \left\| x - \mu_i \right\|_2^2 \tag{5}$$

c_i represents the i-th cluster, and μ_i represents the cluster center corresponding to the i-th cluster.

In the whole process, the user's behavior path, that is, the report of user data buried log, plays a very important role in the recommendation system. Figure 3 below is the main workflow of personalized video recommendation in the platform, which is divided into four modules: student user management, domain knowledge model, video resource module and recommendation module.

Within the whole module, the user management module primarily recommends content through the information of students' school status for the first time, and then analyzes the user's behavior characteristics in the later period to identify the user's interest model. The purpose of the domain knowledge model is to build the relationship between the contents of the curriculum system. The video resource module mainly forms the evaluation system of video resources through the explicit and implicit feedback behavior of users. The recommendation module is the core of the whole system, which, through certain processing, serves as a bridge to connect users with video resources and filters and sorts them to form the final result.

Figure 3. Video recommendation system flow



The user's reaction to behavior is different, so the interest influencing factor will be determined according to the user's investigation in the early stage, which is defined as k, and the corresponding end-user interest for the user's interest i is calculated as follows:

$$W_i = \sum_{b \in B} w_{ib} * k_b \tag{6}$$

The CF preference value of user u for the course is defined as follows, and the final result is obtained by weighting the scores of k users with the similarity, where $r\left(v,i\right)$ represents the score of user v for the course i.

$$pref_{CF}\left(u,i\right) = \frac{\sum_{v=1}^{K} simi\left(u,v\right) * r\left(v,i\right)}{\sum_{v=1}^{K} simi\left(u,v\right)} \tag{7}$$

Given the feature vector of document I, the central vector of cluster C is c, and the similarity between document I and cluster C is defined as:

$$sim\left(d,C\right) = \frac{d * c}{I\left\|d\right\| * \left|c\right|} \tag{8}$$

Two distance thresholds T_1, T_2 of the Canopy algorithm are calculated, and the Canopy algorithm is used to determine the initial clustering of users based on the user attribute rejection matrix, and to determine the cluster number k, where $T_1 = 2T_2$ is set. The calculation method of T_2 is shown in the following formula:

$$T_2 = \frac{2}{n\left(n+2\right)} \sum_{i=1}^{n} \sum_{j=1}^{i} D\left(x_i, x_j\right) \tag{9}$$

The distance is calculated by Euclidean distance.

In the process of generating user preference tags, the vector of each secondary classification tag in the topic space is calculated by using the topic vector space extracted in the above algorithm. The similarity is sorted to determine the secondary classification with high similarity to the user as the user's interest tag (Wu et al.,2020)

The formula for calculating the feature vector θ_t of tag t and the similarity between user u and tag t is as follows, where n_t is the total number of courses classified by tag t.

$$\theta_t = \frac{1}{n} \sum_{i=1}^{n_t} \theta_i \tag{10}$$

RESULTS, ANALYSIS, AND DISCUSSION

In this experiment, a class of students was randomly selected from the school as the experimental object. After investigating the students' historical comprehensive ability, the author divided 40 students into two study groups. They were classified as the experimental group and the control group according to their historical comprehensive ability and the reward method of conduct points was used to maximize the mutual assistance and supervision of the groups.

In order to investigate students' acceptance of a digital classroom, the author designed a digital classroom satisfaction questionnaire and distributed it to the experimental subjects. Forty questionnaires were distributed, with a recovery rate of 100%. The survey results are shown in Figure 4.

Compared with the traditional lecture method, the digital teaching of history is welcomed by most students, with 79.92% of students indicating the digital teaching mode of history course is helpful for their history study and they hope to continue to learn history in this way. In addition, 46.69% students generally reflect that the digital teaching mode of history course is more conducive to their understanding of history and expanding their extracurricular knowledge than the traditional classroom.

In response to the question, "Do you think digital classroom is helpful for mastering knowledge?" 53.39% students think it is very helpful, 30.43% students think it is helpful, 13.17% students think it is average and 3.01% students think it is not helpful. The survey results are shown in Figure 5.

Figure 4. Students' satisfaction with digital classroom

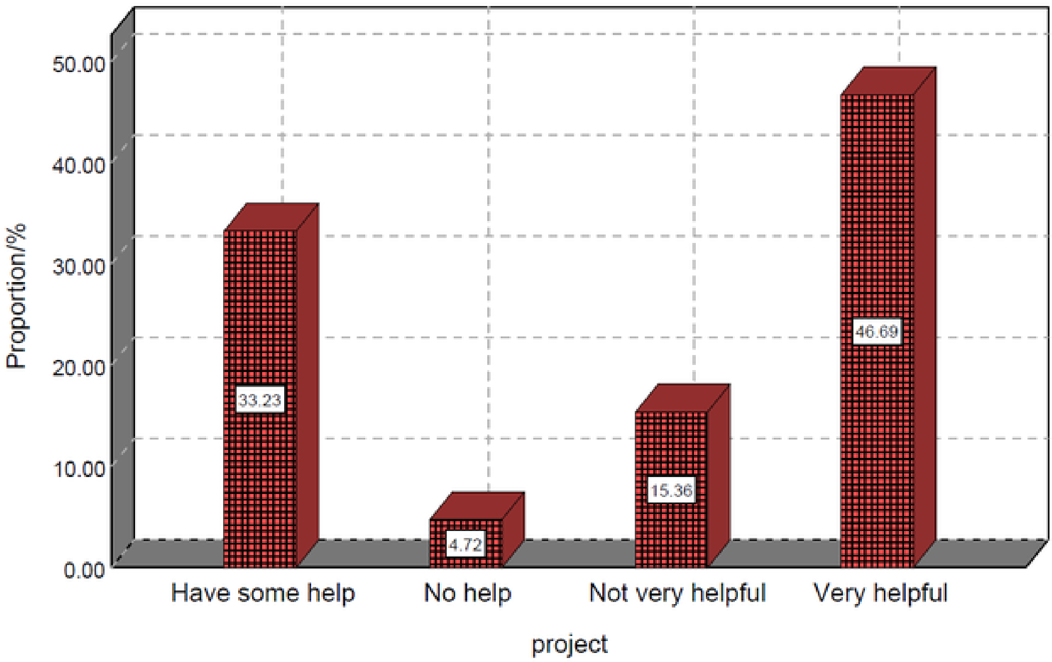
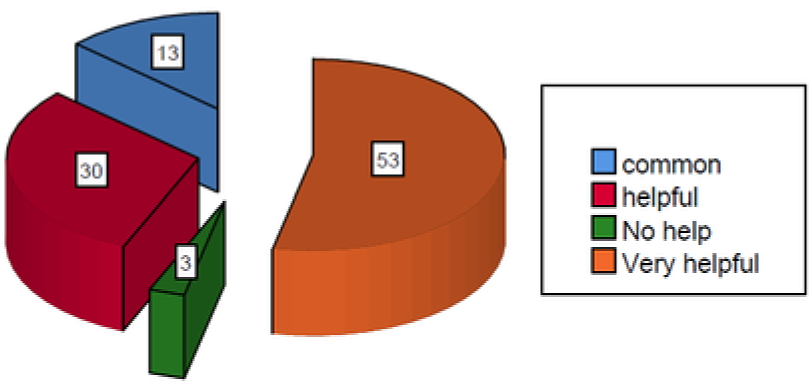


Figure 5. Survey chart of improving the recognition of learning effect



Based on the results of the questionnaire and the contents of student interviews, students' acceptance of the digital classroom is relatively high. However, some students raised concerns, such as that in the process of group cooperation and inquiry, some students did not participate, and they were dissatisfied with the way of dividing groups directly according to seats and would prefer to form groups freely.

The Williams Creativity Assessment is a psychological test aimed at assessing individuals' tendencies and abilities in creative thinking and problem-solving. The Williams Creative Aptitude Test can be used in schools or educational institutions to help teachers and educators understand students' creative tendencies, better adjust teaching methods and curriculum, and promote creative thinking and innovation. During the experiment, the students in the experimental group and the control group were tested for Williams' creativity tendency before and after the experiment. After the experiment, the data before and after the experiment were sorted in MS Excel and analyzed by SPSS statistical software. There are 50 items in Williams' creativity tendency test scale, including adventure, curiosity, imagination, and challenge. Those with a test score of 135 or above indicate excellent creativity and a high level of creative thinking. Test scores of 120-134 indicate the students' creativity is good and creative thinking level is high. Test scores of 90~119 indicate the students' creativity is average and creative thinking level is medium. A test score below 90 shows that creativity is poor and the level of creative thinking is low.

The scores of Williams' creativity tendency test of students with different cognitive styles in the experimental group after the experiment were counted by Excel, and the average scores of students were compared. The results are shown in Figure 6 below.

In the Williams creativity tendency test scores of field-dependent students and field-independent students in the experimental group, the average total score of field-independent students is between 110 and 120, and the average total score of field-independent students is above 120. The thinking level of field-independent students in the experimental group reached a high level after the experiment.

Using SPSS statistical software, the scores of Williams' creativity tendency test after the experiment of field-dependent students and field-independent students in the experimental group were tested by independent sample T, and the test results are shown in the following Table 1.

The average score of the field-dependent students' creativity tendency test in the experimental group is 114.23, and the average score of the field-independent students' creativity tendency test is 126.85. There are obvious differences in the total score and four dimensions of creativity tendency test between

Figure 6. Williams' creativity tendency test results

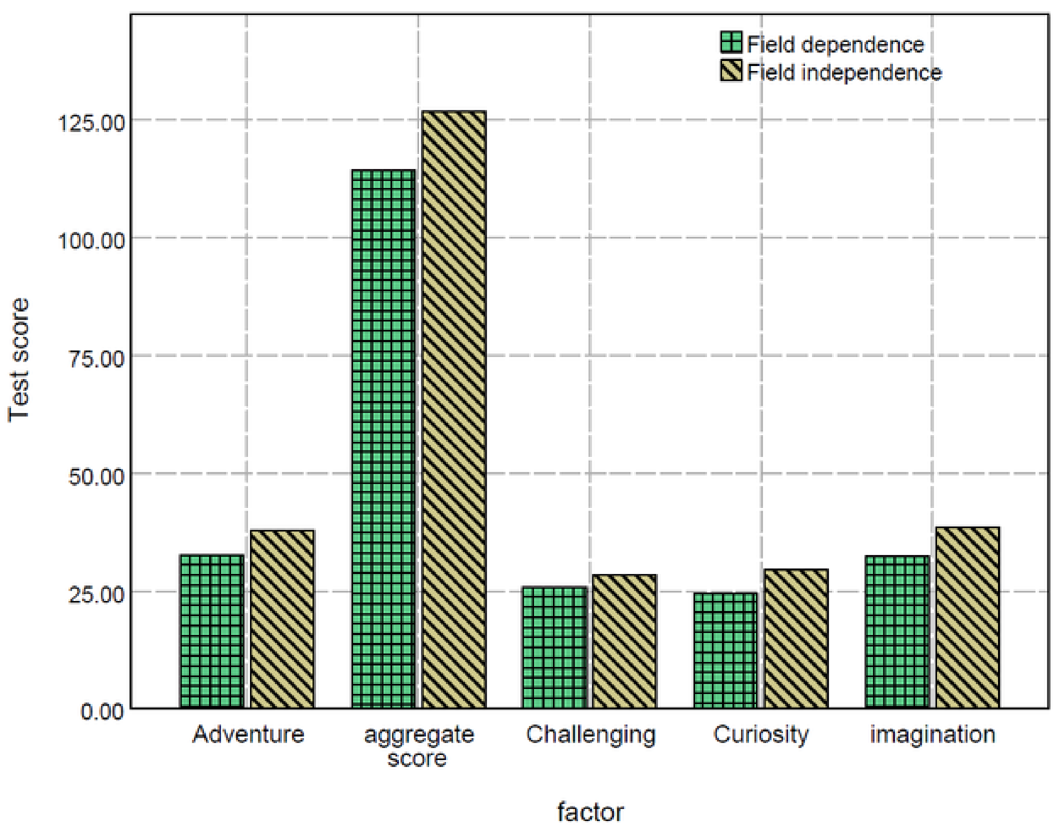


Table 1. Test results

Factor	Field dependence (n=20)	Field independence (n=20)	t	Sig
Aggregate score	114.23±3.655	126.85±3.639	-4.598	0.000
Adventure	32.51±2.154	37.95±2.854	-2.382	0.006
Curiosity	24.53±3.254	29.47±2.891	-1.399	0.000
Imagination	32.45±3.584	38.52±2.786	-3.773	0.009
Challenging	25.87±4.176	28.49±3.11	-5.345	0.033

field-dependent students and field-independent students in the experimental group, and the scores of field-independent students after the experiment are higher than those of field-dependent students.

By preprocessing and cleaning the data set obtained by the data crawling platform and the rule-base data set based on the advanced relationship of the course, the processed data set was used as experimental data, and then the intelligent recommendation method of history course proposed in this paper was verified by using this data. The experimental hardware environment in this paper was: processor: Intel(R) Core (TM)i5-4200M, memory: 8G, hard disk: 1T.

Because this study focused on learners and selected advanced courses, only 80% of learners' course selection set was randomly divided into the training set and 20% was used as the test set, while learners' learning duration, course discussion, and certificate acquisition set were not divided. Based on this, the intelligent recommendation method of history courses proposed in this paper was used to carry out experimental verification on training sets and test sets. The number n of course recommendations was changed and the recommendation accuracy and recall rate were calculated, with the results are shown in Figure 7 and Figure 8 below.

Figure 7. Accuracy under different n values

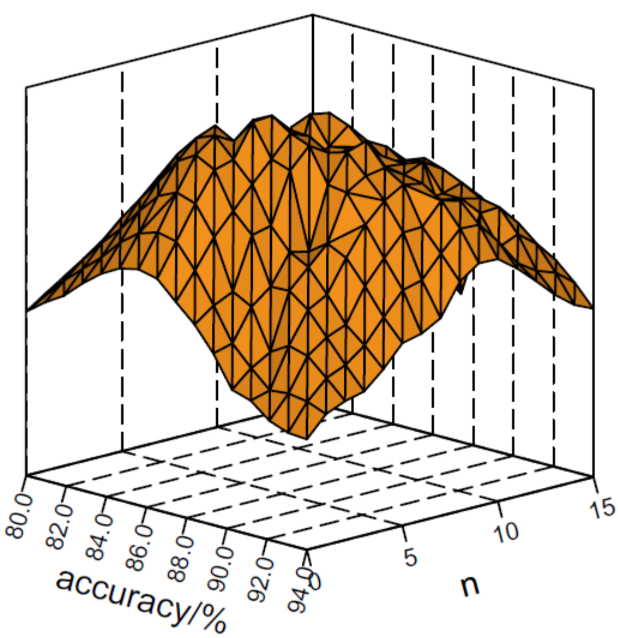
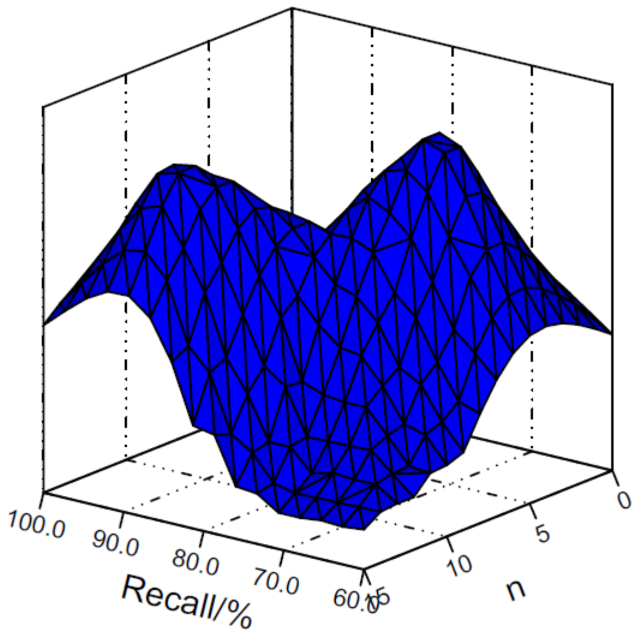


Figure 8. Recall rate under different n values



Results indicate that the learner-led course recommendation methods proposed in this paper increase with the increase of the number of course recommendations n , and they are all greater than 0. When the number of course recommendations is $1 \leq n \leq 10$, the average accuracy rate is 87.346%. As a whole, the recall rate increases with the increase of the number of course recommendations n, and the minimum recall rate is 65.92%.

Satisfaction analysis as determined by whether students meet the learning objectives, whether they meet the learning interests, and whether they meet the recommendation results (the evaluation results are yes or no), is shown in Table 2 below.

The above experimental data show that the intelligent recommendation method of history courses proposed in this paper can better perceive the healthy state of learners' course selection and accurately predict the leading courses that learners need to strengthen their study according to the perception results and recommendation rules, so as to guide learners to choose and study courses scientifically and ensure the integrity and robustness of their course knowledge.

CONCLUSION

With the in-depth development of curriculum reform, traditional classroom teaching methods are far from meeting the development needs of teachers and students. Given such limitations, effective teaching methods must be studied. In this study, the teaching of history courses via digital technology

Table 2. Satisfaction analysis

Algorithm	Learning target (%)	Learning interest (%)	Degree of satisfaction (%)
Traditional algorithm	56.38	62.17	71.96
Algorithm proposed in this paper	71.08	79.32	94.51

was examined. This paper presents the design of digital resources for history courses and analyzes the learners' mastery of the necessary knowledge, skills, and learning habits as well as the key contents of training courses and teaching purposes. On this basis, a history course resource recommendation algorithm is designed and implemented. Compared with the traditional method of lecture-based instruction, the digital teaching of history course is welcomed by most students, with 79.92% students indicating the digital teaching mode of history course is helpful for their history study and they hope to continue to learn history in this way. Research has shown that the development and use of digital teaching resources have potential in education and can improve learning experiences. Secondly, learner led course recommendation methods have shown good results in course recommendation, emphasizing the importance of personalized education. Therefore, educational institutions should continue to invest in and support the development and implementation of digital teaching resources to meet students' needs for emerging educational technologies. This includes creating more digital history course resources so that students can learn history knowledge more flexibly. Teachers and educators should actively participate in the design and evaluation of digital teaching resources to ensure their quality and applicability. They can also utilize learner led course recommendation methods to better meet students' personalized needs, and further research can explore how to further improve the design and interactivity of digital history course resources to increase student engagement and learning outcomes. In summary, the application of digital teaching resources in history courses is expected to bring positive changes to education, but sustained efforts and cooperation are needed to ensure its maximum benefits.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The author declares that they have no conflicts of interest.

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