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A Study on the Impact of Digital History Education Resources on Teaching in Secondary School History Classrooms

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Abstract With the arrival of the digital era, the digitization of history education resources has become an important means to improve the quality of classroom teaching. Through experimental design and data analysis, this paper explores the application effect of digital history education resources in secondary school history classroom teaching. The study adopted a learning recommendation model based on knowledge graph and conducted a semester-long teaching experiment in Shanghai A Middle School. The experimental results showed that the experimental class using digital resources demonstrated significant advantages in learning motivation, learning achievement and classroom participation. Specifically, the final grades of the experimental class increased by 5 points on average, and the grades were more centrally distributed with lower standard deviation, showing better learning effects and higher learning stability. This paper also analyzes the accuracy of different recommendation algorithms by comparison, proving that the proposed algorithm is superior to other algorithms in terms of recommendation accuracy, with lower MAE and RMSE values, respectively, verifying the feasibility and effectiveness of the application of the model in history education. The study shows that digital history education resources can not only enhance the interactivity of classroom teaching, but also enhance students' interest in learning and improve their mastery of history knowledge.

Index Terms Digital history education resources, knowledge graph, recommendation algorithm, learning achievement, classroom engagement, teaching model

I. Introduction

The rise and development of digital resources is supported by economic development and scientific and technological progress, and it is also inseparable from the education sector's vigorous promotion of education informatization [1]. A number of documents proposed to promote the combination of modern technology and education, promote the development of education informatization, and implement the strategy of science and education to develop the country [2]. With the implementation of relevant education policies, the software and hardware of education informatization have gradually developed, and the accompanying digital resources have also gradually emerged, and are more and more used in classroom teaching and daily learning [3]-[5]. With the deep integration of computer network technology and the field of education, there are also many digital resources dedicated to education and teaching, the digital level of teaching resources is getting higher and higher, the main teaching resources used in history teaching is also in the process of gradual development from the original single paper resources, to the development of multiple digital resources [6]-[8].

Since the 21st century, computer and network information technology has developed rapidly, and the degree of education informatization has been greatly improved. Especially since 2017, the development of computer and network technology can be described as a rapid development, and China has entered the period of education informatization 2.0 [9], [10]. The popularization of the Internet and wireless networks has made digital resources available everywhere. From the viewpoint of history subject, a huge amount of digital resources have been accumulated from the beginning of the 21st century to the present, and history teaching possesses new possibilities, and various types of digital resources, such as audio, video, website, software, etc., have greatly enriched the history classroom [11]-[14]. On the one hand, the application of digital resources can not only vividly present text, pictures, audio and video and other types of historical materials, but also help to render the atmosphere of the history classroom, create historical situations, stimulate students' emotions, which is very conducive to the cultivation of students' core literacy [15], [16]. On the other hand, in the application process of digital resources, teachers can also consciously cultivate students' ability to search, identify and apply digital resources, subconsciously help students establish a big resource learning concept and broaden the spatial and temporal boundaries of their learning, which will be conducive to the long-term development and lifelong development of students [17]-[19]. Therefore, the application of digital resources in history teaching is in line with the requirements of modernization of education, as well as the basic requirements of the history discipline in the cultivation of the core qualities of the discipline.

With the rapid development of information technology, digital educational resources have gradually entered the education system at all levels, especially in history education, where digital resources provide a rich complement to traditional teaching methods. In recent years, the resource recommendation system based on knowledge graph has become an important tool for improving teaching quality. Through the intelligent management and recommendation of learning resources, it can not only help students customize their learning content according to their personal interests and needs, but also enhance the interactivity and participation in the classroom. In secondary school history teaching, the traditional teaching mode is often relatively single, lacking targeted learning resources, and the introduction of digital resources can realize the development of students' personalized learning path through the accurate recommendation system, thus enhancing their learning effect. However, the application of digital resources in teaching is not a one-step process, which involves the digitization of teaching content, the acceptance of teachers' technology and students' learning styles and other factors. Therefore, exploring the actual impact of digital history education resources on classroom teaching and its optimization path has become a hot spot of current research.

This paper compares the effects of traditional teaching and the smart classroom teaching mode based on digital history education resources through experimental design. In the experiment of Shanghai A Middle School, the study selected two classes as the experimental subjects, used digital resources for teaching, and compared the learning outcomes under the traditional teaching mode. The effectiveness of the application of digital educational resources was assessed through comparative analysis of factors such as final grades, student motivation and classroom participation. The study also uses knowledge mapping and recommendation algorithms to provide a new methodology in enhancing students' personalized learning.

II. Knowledge graph-based digitization of history courses and source recommendation

II. A. Creation of a Knowledge Map for History Education Programs

II. A. 1) Extraction of entities

Taking the entities in the curriculum knowledge graph as the knowledge points, in the process of analyzing the concepts in the teaching resources, it can be realized by the way of entity-based extraction. The article utilizes web crawlers to extract and process the learning resources, where the keywords are the word frequency TF values in the text inverse frequency IDF:

$$TF_i = \frac{n_{ij}}{\sum_k n_{kj}} \tag{1}$$

$$IDF_i = \log \frac{|D|}{1+\left|\{j : t_i \in d_i\}\right|} \tag{2}$$

$$TF-IDF = \frac{TF_i \cdot \log = \left(\frac{|N|}{1+\left|\{j : t_i \in d_j\}\right|} \right)}{\sqrt{\sum_{j=1}^{n} \left[TF_i \cdot \log = \left(\frac{|N|}{1+\left|\{j : t_i \in d_j\}\right|} \right) \right]^2}} \tag{3}$$

Eqs. (1), (2), and (3) where n_{ij} is the word frequency of word t_i in learning resource d_j, $|D|$ is the total number of documents in the course learning resource, and $|N|$ is the number of words in the learning resource.

II. A. 2) Extraction of relationships

This step enables problems such as semantic links between entities to be solved, Word2Vwc uses training to map words and phrases to become K-dimensional entity vectors, and then uses the distance between individual words to make a judgment on semantic similarity, and also creates hierarchical relationship trees. Define the relationship of knowledge points with the actual requirements.

II. A. 3) Ontology construction

The article selects a C programming course in the computer science program to create an ontology using the Protege tool.

II. B.Knowledge graph based resource recommendation modeling and training

II. B. 1) User interest and needs analysis

There is a wide range of similarity between user interests and resources and there are more algorithms. The keywords of the article are different user interest characteristics, and the user characteristics are shown after focusing on each item. The text similarity is calculated using word vectors and the similarity is defined as:

$$Interest(u,i) = \frac{1}{|N(u)|} \sum_{j \in N(u)} \frac{\overline{w_i} \cdot \overline{w_j}}{|\overline{w_i}| \cdot |\overline{w_j}|} \tag{4}$$

The u in equation (4) refers to the target user and $|N(u)|$ refers to the number of historical learning resource collections. Using the above formula can calculate the user's interest and resource similarity, the higher the similarity value, the more matching the needs are and can be recommended to the user.

II. B. 2) Recommendation Algorithms for Beginners

For beginners, the system is unable to recommend data for them, so it is necessary to consider the “cold start” problem. When the system is in “cold start”, it can not directly analyze the user's knowledge needs, level and interests, so it is necessary to analyze the recommendation algorithm for beginners.

The article is based on the user's independent choice of information and reasonable recommendation of learning resources, in the beginner will be keywords into the platform, can be calculated through the knowledge graph to match the degree, according to the keywords to effectively expand other knowledge content. This kind of knowledge content and resources are more and more extensive, the key knowledge to select, so as to create a user knowledge base, and then combined with the knowledge base there is a high degree of similarity of the resources to realize the recommendation.

II. B. 3) Modeling of knowledge graphs

In online learning platforms such as MOOC and Superstar Learning Access, the core concepts of resources can be defined in terms of test types such as courses, resource sites, exams and transcripts, as well as learning platform registration and student information.

Data are extracted and stored through OULAD datasets, including learner, assessment and course datasets, with a total of 11,243,832 learner and system interaction information. All entity data are extracted according to the ontology concept and associated with all entities in the knowledge graph, resulting in a knowledge graph of 267381 entries and 221455 entities, and the related data are stored in the graph database.

II. B. 4) Training of graph embedding models

For the knowledge graph in digital environment can show the correlation between learners and learning resources and society, the network topology should be analyzed in the graph embedding process. Improve the network invisible features to create the overall network topology of knowledge graph, and utilize Node2vec algorithm to realize the graph embedding training.

By this algorithm can randomly wander with depth (DFS) and breadth (BFS) priority sampling strategy. Breadth-first sampling focuses on source nodes neighboring nodes and depth-first sampling refers to source nodes and neighboring coverage nodes. Sampling by random wandering thus results in node path combinations, creating a model based on the word vector approach to derive a network node representation. The rule constraints are used in the random walk, and the two dynamic adjustment methods are combined to show the characteristics of the two to improve the network embedding effect.

By Node2vec algorithm [20] to be calculated for the node to a certain neighbor transfer probability, the result of the calculation is added to the graph and the random walks are stored according to the walks. Initialization is empty, after cycling the nodes to generate the number of walks, i.e., so that each node can become an initial node, thus generating random walks walks, which are trained using the random decreasing method.

II. B. 5) Recommendation process for history learning resources

Graph embedding and knowledge graph are combined with each other to quit the new personalized learning recommendation method, and the process is:

(1) The interaction information in the system is extracted, and then the online learning knowledge graph is created. After that, the knowledge graph is trained with graph embedding algorithm to derive the embedding model. Numerical computation with the embedding model improves the computational efficiency.

(2) Use graph matching to derive similar subgraphs, and then, filter the elements in the subgraphs to derive a collection of personalized similar learning resources.

(3) Since there is a group tendency of learners in the learning process, learner clustering and grouping is realized based on learning style characteristics, so as to calculate the user's interest in the resources.

(4) Calculate the learner's interest degree in the collection of similar resources and sort them to get the collection of learning resource recommendations.

II. C.Experimental Design and and Analysis

II. C. 1) User rating calculation speed and accuracy test

The algorithm in this paper uses neural networks to realize automatic user scoring, and in order to verify the speed and accuracy of the algorithm in this paper, 10 users, numbered 1-10, were randomly selected from a large number of users using digital history education resources.Since simply calculating the error rate does not better reflect the scoring ability of the algorithm in this paper, the scoring data also needs to be calculated with the Mean Absolute Error (MAE) value, and at the same time the scoring runtime is recorded Time. Running time is less, it means that the calculation of the user rating speed; error rate is low, indicating that the scoring rate is high, and the MAE also reflects the scoring rate of this algorithm. When the MAE is the same as the miss rate, it indicates that each miss is minimized. The experimental results are shown in Table 1. The table shows that the highest running time of this paper's algorithm in calculating the user rating is 0.035s, which indicates that the algorithm is fast in rating. The error rate in the table fluctuates around 5%, the error rate is low, proving that the algorithm calculates the scoring accuracy is good, and the MAE is equal to the value of the error rate, which indicates that the prediction error of the extracted samples is minimized. In summary, the use of the algorithm in this paper has the advantages of fast running speed and high accuracy.

Table 1: User scoring speed and accuracy

User	Error rate	Forecast rating MAE	Running time /s
1	4.76%	0.0476	0.035
2	4.76%	0.0633	0.016
3	6.33%	0.0476	0.017
4	4.76%	0.0633	0.027
5	6.33%	0.0633	0.035
6	6.33%	0.0297	0.016
7	2.97%	0.0476	0.017
8	4.76%	0.0633	0.016
9	6.33%	0.0476	0.035
10	4.76%	0.0476	0.027
11	5.21%	0.05209	0.024

II. C. 2) Accuracy test of different recommendation algorithms

From this digital history education resource website, some digital history education resource websites are randomly selected to form a dataset, and the obtained data are randomly divided into two groups, which can not be repeated, one group is the training set accounting for 80%, and one group is the test set accounting for 20%. In order to verify the accuracy of the algorithm in this paper, the operational mean absolute error (MAE) and root mean square error (RMSE) are used as experimental indicators. The experimental control algorithms are RippleNet algorithm [21] and MKP algorithm, and the experimental results of these two algorithms are compared with the algorithm of this paper. The experiment uses these three algorithms to complete the recommendation of digital history education resources. In order to verify the accuracy, the mean absolute error MAE and root mean square error RMSE need to be calculated from the acquired scoring data, and the comparison is shown in Table 2 and Table 3.

As can be seen from the table, when the value of the target user is 6, the MAE and RMSE values of the three algorithms are the smallest, indicating that the error is the lowest at this time, and the results of the three algorithms recommending digitized resources are the best. Comprehensive observation, this paper's algorithm has the lowest error compared with RippleNet algorithm and MKP algorithm, which proves that this paper's algorithm can accurately find the target user and recommend the digital resources accurately.

Table 2: The MAE value test results of the three recommended algorithms

Algorithm \ Number of users	2	4	6	8	10
This algorithm	0.801	0.790	0.778	0.783	0.784
RippleNet	0.826	0.821	0.815	0.835	0.843
MKP	0.939	0.923	0.913	0.960	0.993

Table 3: The RMSE value test results of the three recommended algorithms

Algorithm \ Number of users	2	4	6	8	10
This algorithm	1.01	1.01	1.00	1.05	1.02
RippleNet	1.03	1.03	1.03	1.04	1.05
MKP	1.15	1.14	1.13	1.16	1.18

III. Impact analysis of digital history education resources

III. A. The construction of intelligent classroom teaching mode in junior high school history

III. A. 1) Pre-course

(1) Initial analysis of learning situation

According to the knowledge graph-based learning recommendation model before teaching the activity is to attract students' attention, teachers should analyze the students' learning situation according to the students' learning level, age, psychological characteristics, cognitive level and the existing learning situation, clarify the teaching key points and preliminary design of the teaching process.

(2) Resource Release

First of all, teachers in the smart classroom platform to select the relevant historical learning materials, the selection of materials should be closely around the teaching content of the important and difficult points and then select the release of the platform to the student side, for the more difficult to understand the historical events can be used in the way of the background to expand the students to do pre-study, so that students grasp the relevant historical background for the class to lay a foundation for learning. Secondly, the teacher assigns pre-study tasks through the homework function of the smart classroom, the students accept the pre-study tasks and then complete the pre-study tasks carefully, and the intelligent analysis of the smart classroom quickly understands the pre-study situation of the students.

(3) Re-analysis of learning situation

Teachers can obtain the analysis of students' learning situation with the technical support of smart classroom, and then analyze the learning situation again with the students' learning level, age, psychological characteristics and existing experience.

(4) Teaching design

According to the learning level of the learners and the course content, the teaching process should be optimized and improved again, and in the teaching process design, the classroom interaction, problem release and group discussion should be formulated well in advance, and the smart classroom platform should be used to make the corresponding teaching preparations.

III. A. 2) In class

(1) Classroom introduction

According to the ARCS model the activities before teaching focus on attracting students' attention and stimulating learning interest. Teachers can combine the smart classroom platform to create a situation, using interesting stories in the background of the history text cleverly designed classroom introduction, so that students in the process of experiencing the activities to arouse the attention and desire to explore.

(2) Issuing tasks

At this stage, teachers should match students' motivation and help them establish a sense of familiarity with the historical knowledge in the text, so that they can actively participate in the process of learning new knowledge and further strengthen their motivation.

(3) Follow-up testing

After the completion of classroom teaching, teachers need to carry out certain tests on the effectiveness of teaching, and test questions are one of the effective ways of testing. Teachers release test questions to students through the Changyin Smart Classroom, and after students complete the test, teachers can quickly access the students' intelligent answer reports, which help teachers fully and accurately grasp the learners' answers and adjust teaching in a timely manner.

III. A. 3) After school

Teachers use the homework function of Smart Classroom to release personalized learning materials to students, including learning packages to expand knowledge after class or test questions for classroom content. After-school homework is the teacher's feedback on students' homework, to accurately push their weak knowledge of the exercises, to help students further consolidate and deepen their understanding of the knowledge points.

Teachers are required to summarize and reflect after class, and the Smooth Speech Smart Classroom makes the classroom of junior high school history smarter and more efficient. Teachers and students can get intelligent learning analysis report, teachers can adjust the teaching to promote students' knowledge mastery, students can also accurately grasp their own learning status, targeted learning. After the class, teachers should analyze and reflect on the problems of the whole teaching process, improve the deficiencies in a timely manner, and prepare for the next class.

III. B. Experimental design

III. B. 1) Experimental background

The teaching experiment of this paper is based on Shanghai A Middle School, which is a national special education school and is equipped with a full range of Changyin Smart Classroom facilities, providing better hardware and software support for this study. Relevant technicians from KDDI have trained the main teachers of the school on the hardware and software operation skills of the smart classroom platform, and the teachers are more skillful in applying the tablet and the smart classroom software for teaching, and the students are interested in the smart classroom and most of them are more familiar with the use of tablets, and they are able to skillfully use the student side for daily learning.

III. B. 2) Experimental Objects

A semester teaching experiment was conducted in Shanghai A Middle School. Before the experiment, the current status of students' motivation level and their academic performance were statistically analyzed, and it was found that there was no significant difference between the motivation level and academic performance of students in the two classes, the first year (6) class and the first year (7) class. In addition, both classes were taught by the same teacher and had the same pace and content of the history curriculum. Therefore, these two classes were selected as experimental subjects for this study. Class 7 was taught using the middle school history smart classroom teaching model based on the knowledge graph-based learning recommendation model constructed in this study, and was the experimental class; class 6 was taught using the traditional teaching method, and was the control class.

III. C. Findings and analysis

III. C. 1) Normality test

When carrying out the description of the overall data, it is often the first step to make certain assumptions about the distribution pattern of this sample, such as assuming that the distribution of grades is normal. The results of the one-sample Kolmogotov-Smirnov test are shown in Table 4, from which it can be seen that the mean is 75.21, the standard deviation is 14.58, and the sig value is less than 0.05, which rejects the original hypothesis and indicates that the sample is non-normally distributed.

Table 4: Single-sample kolmogotov-smirnov test

Null hypothesis	Test	Sig.	Decision maker
The distribution of scores was normal, with an average of 75.21 and a standard deviation of 14.58	Single sample kolmogotov-smirnov test	0.001	Reject the null hypothesis
The progressive significance is shown, and the significance level is 0.05			

In order to more intuitive observation, pp charts in SPSS are also often applied to determine whether the variables obey normal distribution, if the data obey normal distribution, the data points in it should be basically coincident with the theoretical straight line (diagonal), the experimental results are shown in Figure 1. As can be seen from the figure, there is a significant difference between the actual and theoretical distributions of the grades.

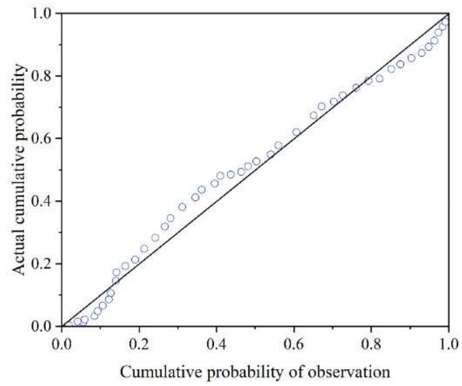


Figure 1: Positive state P-P diagram of achievement

Figure 2 shows the distribution reflecting the difference between the theoretical and actual values calculated from a normal distribution, i.e., a plot of the residuals of the distribution. If the data obeys a normal distribution, the points of the data should be relatively evenly distributed above and below the line y=0. As can be seen from the graph, the absolute value of the residuals exceeds 0.1 at its highest, so it can be judged that the grades do not obey a normal distribution, i.e., the distribution of the total semester grades of the two classes does not obey a normal distribution.

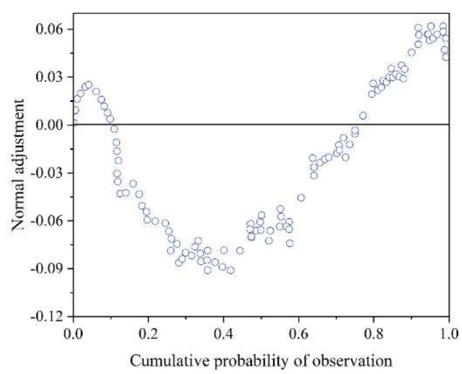


Figure 2: The trend of the trend is the positive state of the P-P diagram

III. C. 2) Sample K-S test

Considering whether the distribution status of students' grades is reasonable, i.e., whether they are normally distributed or not, this paper conducted K-S test on the data as shown in Table 5. As can be seen from the table, the probability of significance of the overall achievement of the sample $p=0.0088$, $p<0.05$ and close to 0, indicating that the sample basically obeys a normal distribution. This test on the normal distribution of grades facilitates teachers to select the best and screen the laggards. The test results show that more than 60% of the students scored more than 80 points, which can be seen that this course basically meets the teaching requirements.

Table 5: The single sample, kormogoov, was tested

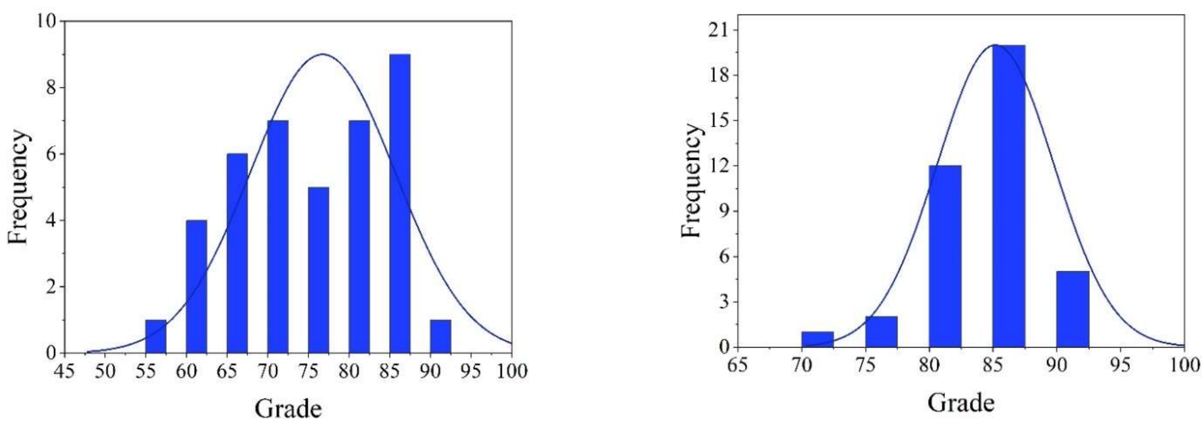
Test type		Serial number	Final grade
Case number		80	80
Normal parameter a and b	Mean value	41.23	83.1147
	Standard deviation	25.185	9.08732
Most extreme interpolation	absolute	0.071	0.121
	positive	0.071	0.102
	negative	-0.071	-0.149
Inspection statistics		0.069	0.159
Progressive prominence (Sig.)		0.203c,d	0.000c

Notes: a. Test distribution is normal; b. Calculated from the data; c. Riley's significance correction; d. This is the lower limit of true significance.

III. C. 3) Sample t-tests

In this paper, a t-test was conducted on the final grades of Chinese History of two classes in order to compare the means of the discussion grades of the two classes in the program, so as to test whether there is a significant difference between the grades of the two classes and whether the final grades were affected by the smart classroom teaching mode. First of all, the basic analysis of the two classes' grades was carried out, and it was found that the mean score of the control class was 75.48, with a standard deviation of 8.47, and the mean score of the experimental class was 85.19, with a standard deviation of 5.33. The difference between the lowest grade of the two classes was 15 points, the difference between the highest grades was 10 points, and the difference between the mean grades was 5 points, so it can be initially determined that the experimental class had better grades. The comparison of standard deviation also reveals that the experimental class is more stable. Then the sample t-test of the two classes' grades showed that the probability of significance (two-tailed) $p=0.00<0.05$, that is, there is a significant difference between the final grades of English majors in two different directions.

The history final grades of the two classes are shown in Figure 3. From the histogram distribution and the normal distribution curve pattern of the two classes in the figure, we can intuitively see the difference in the performance of the two classes: the control class is obviously more dispersed and has low performance, while the experimental class is obviously more stable and has higher performance. The two classes have the same objective factors, such as lecturers, classroom materials and teaching methods, but there is a significant difference in performance, which suggests that the learning efficiency of the two classes in the course of Chinese History may have been affected by the intelligent classroom teaching mode.



(a) Cross-reference class (b) Laboratory class

Figure 3: Normal distribution histogram of final history scores for two classes

IV. Conclusion

The experimental results show that digital history education resources have a significant positive impact on secondary school history classroom teaching. In the experimental class, students' final grades increased by an average of 5 points, and the standard deviation of the grades decreased significantly, indicating a more stable learning effect. In addition, the learning recommendation model based on knowledge graph effectively enhanced students' motivation and classroom engagement, showing higher learning efficiency. By comparing with the traditional teaching model, the experimental class improved in learning achievement, engagement and motivation, proving the effectiveness and usefulness of digital resources. In terms of recommendation algorithms, the model proposed in this paper outperforms the RippleNet and MKP algorithms in terms of accuracy, and its MAE and RMSE values are lower, respectively, which shows its advantages in the recommendation system. In summary, the application of digital history education resources not only improves the quality of classroom teaching, but also provides students with a more personalized learning experience.

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