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Exploration of Educational Management Strategies and Innovative Development Directions of History Courses in Colleges and Universities in the Digital Era

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Abstract

In this paper, firstly, based on the parametric model, we extracted the factors affecting the satisfaction of the implementation of public policies in towns and cities, and factor analyzed the variables, and established the correlation structure between the variable factors through the logistic distribution function. Then PLS is used to measure the indicator weights, and the parameters are stabilized and predicted to be estimated through iteration. Finally, the satisfaction parameter indicators are repositioned to establish a satisfaction assessment system for public management policy implementation. The results show that the satisfaction assessment system contains a variety of assessment indicators, and the measurement reliability coefficients are all above 0.75. The satisfaction assessment system constructed in this paper can guide the public to set up rational and practical expectations.

Keywords*: parametric model; public policy; factor analysis; satisfaction assessment; logistic distribution function*

Introduction

History course education is an important part of the curriculum system in colleges and universities, and plays an important role in cultivating students' historical consciousness, cultural literacy and critical thinking ability (Li, 2022; Wang, Tan, Cao, Fan, & Deep, 2020). With the advent of the digital era, which has brought many changes to the history course education management, colleges and universities need to adjust and innovate the history course education management strategy in time for the characteristics of the digital era in order to adapt to the development trend of the times (Mai, Sun, Zeng, & Hu, 2023; Yao & Ma, 2021). Students lack initiative and interest in learning history courses, and often just mechanically accept the teacher's indoctrination. At the same time, due to the complicated and abstract content of the history curriculum, it is difficult for students to truly understand and master historical knowledge, resulting in poor learning results (Ding, Wu, & Li, 2022; Meng et al., 2019; Sun, Zhang, & Liu, 2022). Personalized curriculum generation is a new idea to solve this problem, which can tailor the most suitable history course content and learning resources for students according to their individual differences and learning characteristics(Akman, Cairns, Comar, & Hrozencik, 2014).

In the field of history curriculum education in colleges and universities, scholars at home and abroad have carried out a great deal of research work in order to promote the innovation and development of curriculum education. For example, Zhang, H et al. constructed a Jinshang economic history education system by combining fuzzy control with quantum evolutionary algorithm in order to improve the effect of Jinshang economic history education. The system will consist of several sub-modules to provide knowledge points and networks, problem sets, student assignments, and teacher-student interaction sessions for teaching Jinshang economic history (Amen, Faiz, & Do, 2022). Lakshmi, A. V. et al. used whale optimization algorithms to enhance the educational management of college courses by utilizing the humpback whale chase mechanism (Lakshmi & Mohanaiah, 2021), determining a good searching ability, and using teaching-based optimization that can be smoothly plunged into local optimums, combining WOA and TLBO

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features, and actively hybrid WOA-TLBO algorithm to solve educational management optimization challenges (Boni, 2019).

Hou, Y utilizes deep learning to immerse students in knowledge and learning contexts, emphasizes critical thinking, and realizes the intrinsic value of knowledge. Comprehensively consider the complex factors affecting the quality of information technology teaching and use neural network algorithms to stabilize the system and data processing, and finally use the improved BP neural network algorithm to evaluate and predict the quality of the course information technology teaching, and formulate the corresponding teaching process according to the actual needs (Hou, 2022).

Tan, J. make full use of the advantages of artificial intelligence-driven big data-driven system for students to establish a good teaching mode (Tan, 2022), based on particle swarm optimization algorithm to collect students' learning behavior data, extract learning characteristics, and develop towards tailoring to improve teaching quality and efficiency.

In summary, relevant scholars have achieved a series of useful results in their research on history curriculum education in colleges and universities. The main focus is on the design and teaching methods of the curriculum, the development and utilization of curriculum resources, and the application of interdisciplinary education. These research results provide insights in the innovation of history curriculum education in colleges and universities where history courses are generated. This paper proposes to address the dynamic personalized needs of users by capturing and analyzing dynamic data on student characteristics during the learning process to achieve the evolution of personalized learning content.

A personalized initial course is achieved for learners through a hierarchical recommendation algorithm. During the learning process, the learner's personality characteristics are dynamically updated, and the distance between two vectors is measured using the angle cosine through the association between the user's needs and the learning object, which is the value of the personalized historical knowledge course structure. And the association relationship is applied to generate a collection of learning objects that support the target concept set. Finally, by virtue of the correlation matrix between the history course learning resources and the concept sequences, the personalized history course learning content is generated for the learning objects until the learning objectives of the course are finally accomplished (Mostardeiro, Schmitt, & Xavier, 2020).

Structure of history courses in higher education

As a basic long term discipline, history courses in colleges and universities include General History of China, General History of the World, Introduction to History, History of China, History of Western History, General Archaeology, Historical Geography, Ancient Chinese, Introduction to and Selection from Chinese and Foreign Historical and Cultural Canons, and so on. The directions and goals of learning and research are complex and difficult, so first of all, we sort out the structure of the history curriculum in colleges and universities. The history curriculum is divided into content knowledge by experts in the field and its hierarchical structure is expressed in chapters, sections as well as subsections, and the knowledge structure of the discipline of history is expressed in the form of conceptual diagrams (Akıncıoğlu, Akıncıoğlu, Öktem, & Uygur, 2021).

Figure 1 is a conceptual map related to the historical data structure curriculum, which shows the relationship between the curriculum, concepts, and learning objects. Curriculum refers to the systematic learning of a specific subject in a subject area in formal learning, including the knowledge structure system of the course and the synthesis of the learning resources of the course (Wentz, Oldson, & Stricklin, 2014).

Among them, the structure of the knowledge system consists of concepts, which have certain information such as inclusion and constraint relationships, while the sum of learning objects constitutes the learning resources. Different learning objects have different learning objectives, and there is also a correlation between learning objects, which also plays a key role in the generation of learning content (Zhang & An, 2021).

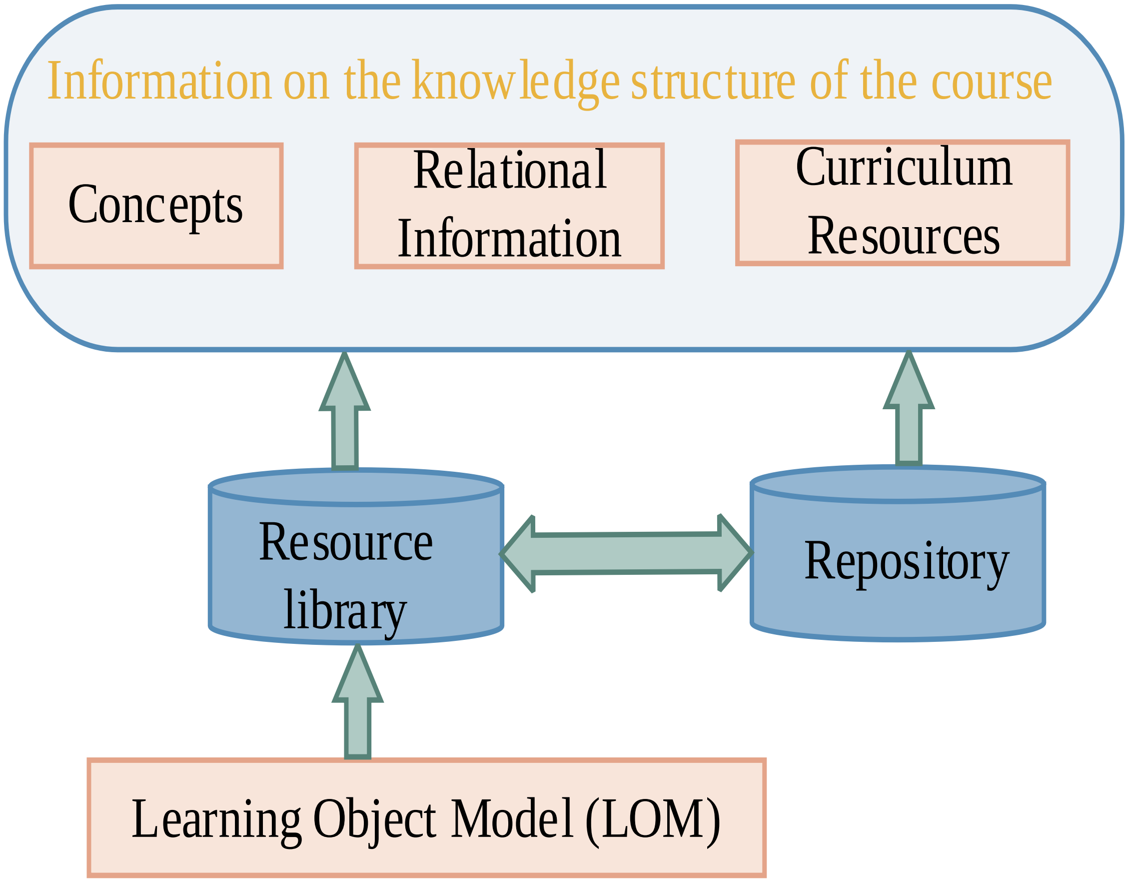


Figure 1 Schematic Diagram of History Course Structure

Learning characteristics of history courses

Dynamic Personality Profile Generation Module

In order to better realize personalized learning, the learner's personality traits need to be dynamically updated during the learning process, including the knowledge information status, the ability information status, and the update of local learning objectives (Mousavi, Rostami, Yousefi, & Dinarvand, 2021). Therefore, a dynamic personality traits generation module is designed, which mainly includes three evaluation function modules. Figure 2 shows the personalized dynamic feature generation model (Granado-Peinado & Huertas, 2023; Leijen, Pedaste, & Baucal, 2022).

(1) Acquiring knowledge information is the learner's current learning progress and feedback on the test questions, applying the Bayesian network method to construct the assessment learning model O matrix, and then using the total score model to calculate the learner's learning score for each concept, thus forming the learner's knowledge vector W.

(2) Acquiring competency information is mainly a dynamic assessment of the learner's competency characteristics currently demonstrated in the course at a certain learning state, i.e., through the probability of cognizing each concept. In this paper, the competence matrix B is applied to characterize the learner's competence.

(3) Acquiring goal information mainly involves dynamically acquiring the learner's current local learning goal information, including making local updates to the learning goal of each concept to be learned next. In this paper, we apply the O matrix to describe the target model, and each component in the matrix represents the learning target of a certain student for a certain concept, and the target form is as defined before.

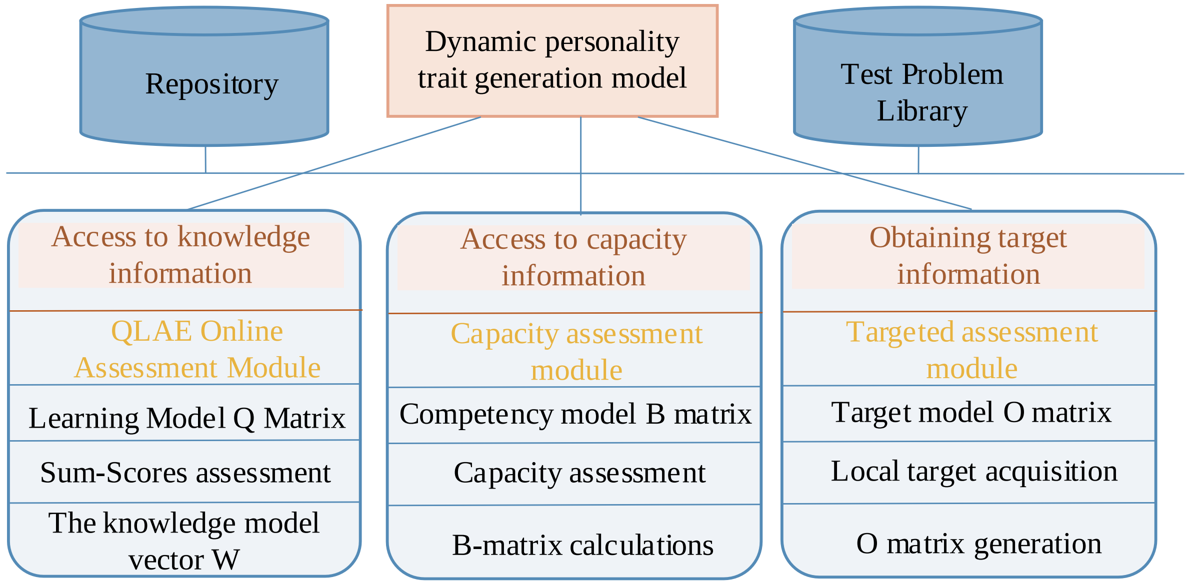


Figure 2 Personalized Dynamic Feature Generation Model

User model

Learner personality characteristics including learner learning history of the course's goal characteristics and other personality characteristics, combined with the characteristics of the collection of learning objects, to establish the association between user needs and learning objects, to achieve targeted adaptive course generation.

User model representation based on vector space model is the most popular representation, which represents the user model as a n-dimensional feature vector $(k_1, w_1), (k_2, w_2), \dots (k_n, w_n)$, with each component consisting of feature keywords and their weights indicating the degree of user's interest in a concept (Edwards, 2022).

The user model first collects relevant data to assess the learner's readiness to take a history course before generating the corresponding knowledge matrix Q and competency matrix B. vector space-based representation is used, and at the same time, since the personalized recommendation algorithm manifests itself as a personalized learning object recommendation during the course generation process based on the learner's learning characteristics, instead of an interest node, it is a learning characteristic node in the user model, and let a certain The concept set in the knowledge structure graph of a course is $C = (c_1, c_2, \dots, c_n)$ (Forester, 2019).

Corresponding to each concept c_1, the corresponding eigenvector (s_i, b_i, o_i) is defined for each of them, where s_i denotes the learner's learning score for concept c_i, whose value is obtained through dynamic assessment during the learning process. b_i represents the learner's assessment of learning ability for concept c_i, which is calculated by the ability matrix. o_i denotes the learner's learning goal for concept k_i, and the student's personality trait vector is obtained as follows:

$$\begin{bmatrix} C = (c_1, c_2, \dots, c_n) \\ S = (s_1, s_2, \dots, s_n) \\ B = (b_1, b_2, \dots, b_n) \\ O = (o_1, o_2, \dots, o_n) \end{bmatrix} \quad (1)$$

Thus using the quaternion form to represent the learner's learning characteristics for concept c_i, the learner personality profile model PLP is represented by a n -dimensional feature vector as:

$$PLP = (C, W, O,, B) = (c_1, s_1, b_1, o_1)(c_2, s_2, b_2, o_2)(c_n, s_n, b_n, o_n) \quad (2)$$

Learning Object Model

During the execution of personalized recommendation algorithms, the representation of the learning object model and the representation of the user's knowledge features are constrained to each other. An index is first created for the resource-concept relationship to represent the set of concepts associated with a learning object in a given collection of resources. Using the most widely used TFIDF method, let the set of concepts in the knowledge structure diagram of a history course be $C = (c_1, c_2, \ldots, c_n)$, and the set of all learning objects in the repository be $R = (r_1, r_2, \ldots, r_m)$, then the correlation coefficient between the ird learning object r_i and the kth concept c_k ^{c_k} is calculated as follows:

$$v_{ik} = tf_{ik} \times \log \frac{M}{df_{ik}} = tf_{ik} \times IDF \tag{3}$$

In Eq. (3), v_{ik} represents the weight of the knd concept in the i rd learning object, i.e., the degree of importance, which is the correlation coefficient between learning object i and concept k. tf_{ik} indicates the frequency of concept k in learning object i. M indicates the total number of learning objects in the course. df_{ik} denotes the frequency of concept k appearing in the history course. Then the correlation between learning object r_i, and the n concepts in the collection of concepts in the history course can be represented by a vector:

$$r_i = (v_{i1}, v_{i2}, \cdots, v_{in}) \tag{4}$$

A matrix of $M \times N$ is used to represent the M learning objects in the course with N conceptual indices, called the indexing matrix:

$$RC = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \tag{5}$$

The correlation between two learning objects r_i, r_j can be measured by the cosine value of two vectors (Fryer, 2019). As follows:

$$r_{ij} = \frac{\sum_{k=1}^{n} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{n} v_{ik}^2 v_{jk}^2}} \tag{6}$$

In this way the degree of correlation between all m learning objects in a history course can be represented by a correlation matrix as follows:

$$\square = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & vr_{mm} \end{bmatrix} \tag{7}$$

Based on the association matrix in the history course, each learning object form is defined as shown in Table 1. The learning object forms of the history course are categorized into metadata, keywords, learning objectives, difficulty coefficients, learning contents, practice contents, and assessment results. The learning objectives are divided into three categories: basic learning, applied learning and exploratory learning, and the difficulty coefficients are divided into levels 1-5. By using methods such as the correlation matrix to build up the learning object forms, the abstract historical knowledge is integrated with the actual context in the learning process, and the assessment results are combined to help students subsequently understand and apply historical concepts in a better way.

Table 1 Definition Form of Learning Objects

Metadata	**ID, Title, Descirption, author, Duration**
Keywords	Keyword feature vectors of learning objects
Learning objectives	Target features, valued as basic learning, applied learning, and exploratory learning
Difficulty coefficient	The difficulty level is described as 5 levels, with values ranging from 1 (easiest) to 5 (hardest)
Learning content	Content pointer, the content information directly presented on the course page
Practice	Practice pointers, practice content after learning
Assess	Evaluation pointer, evaluation results after learning

History course generation based on hierarchical recommendation algorithms

Knowledge structure of the history curriculum

Due to the large number of concepts in the entire historical knowledge base, involving historical knowledge points in various fields, as well as the large number of learning objects in the learning repository, in order to effectively implement the personalized recommendation algorithm and reduce the amount of computation, this paper implements a multilevel recommendation algorithm based on content filtering. The main functions accomplished by each layer of the algorithm are shown in Figure 3 (Zimmerman, 2020). The first layer is the generation of course knowledge structure based on the teacher's overall teaching program, which greatly reduces the search space of the historical knowledge base. The second layer is personalized knowledge structure recommendation based on learner characteristics. The third layer is firstly the learning object recommendation based on the association matrix of concepts and learning objects, and then based on the user's personality traits, the recommendation algorithm of the history course content is applied to match the ability traits and goal traits in the personality traits with the learning object traits, and the learning objects adapted to the learner's personality traits are filtered out.

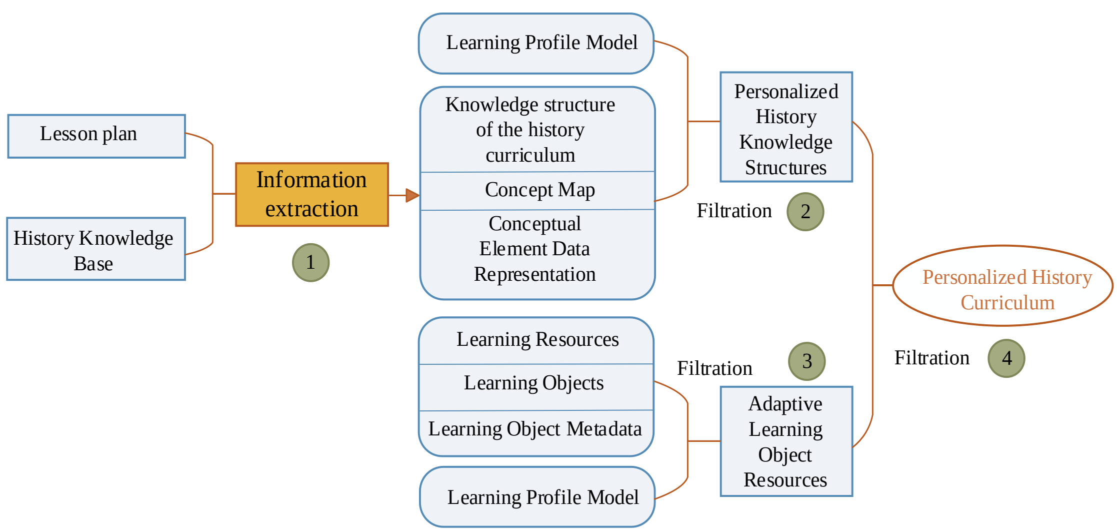


Figure 3 Main Functions of Layered Recommendation Algorithm

Personalize the structure of the history knowledge curriculum

Teachers can only consider the group goal characteristics of the target learners, such as the academic level requirements, the overall average level of knowledge, and the general assessment of the learning ability of the group, etc., when they make the teaching plan of the history course, while in large-scale online learning, the differences in the individual level and ability of each learner can not be reflected in this teaching plan, and teachers can not make different teaching plans for different learners. Therefore, for the individual differences of learners, the adapted learning content and learning styles are different (Heuertz, Paoli, Kllman, & Larsson, 2022). At the beginning of the learning process, history teaching programs need to be generated for different learners, adapted to their initial knowledge background and ability level.

Set the knowledge structure of the course with the set of concepts $C' = (c_1, c_2, \ldots, c_n)$. According to the previous definition, the metadata of the concepts are, id is the concept identification number, dif is the difficulty coefficient, $duration$ is the time coefficient, and $type$ is the type of the concept. The difficulty coefficient is used to weigh the learning difficulty of the concept and match the learning ability of the learner. The time coefficient is used to weigh the length of time needed for concept learning, matching the learner's goal. The type parameter is used to weigh the goal of concept learning, which also matches the learner's goal. The concept type indicates the depth of learning of the concept. Type 1 indicates a basic history course learning concept, Type 2 indicates this applied history course learning concept, and Type 3 indicates this history course exploratory learning.

The personality profile model M_u for a particular user u was determined as shown in Table 2. The target user of the course, i.e., the learner, is modeled as defined previously. Based on the results of the pre-test, the data are collected and analyzed to obtain the learner's level of preparatory knowledge and learning ability before taking the course, as well as his/her learning goals by displaying the feedback, i.e., to obtain the model of personality traits of a certain user u. The goal of the user model definition in this paper is to do adaptive matching of user characteristics with conceptual characteristics and resource characteristics from different perspectives.

Table 2 User Personality Characteristics Sequence

Conceptual features $\boldsymbol{C}$	$\boldsymbol{c_1}$	$\boldsymbol{c_2}$	$\cdots$	$\boldsymbol{c_i}$	$\cdots$	$\boldsymbol{c_n}$
Knowledge characteristics$\boldsymbol{S}$	s_1	s_2	$\cdots$	s_i	$\cdots$	s_n
Capability characteristics $\boldsymbol{B}$	b_1	b_2	$\cdots$	b_i	$\cdots$	b_n
Target Features $\boldsymbol{O}$	o_1	o_2	$\cdots$	o_i	$\cdots$	o_n

Let the knowledge structure of the university history course be $KD' = \{C', R'\}$. For the target user u, its user description based on knowledge characteristics and ability characteristics are respectively:

$$S^u = (s_1^u, s_2^u, \cdots, s_n^u)$$
$$B^u = (b_1^u, b_2^u, \cdots, b_n^u) \quad (8)$$

For n concept in the Conceptual Map of History Curriculum Knowledge, the characterization based on the difficulty coefficient is:

$$Cdif = (cdif_1, cdif_2, \cdots, cdif_n) \quad (9)$$

The set of all possible topologically ordered sequences $\{C_1, C_2, \cdots C_k\}$ based on the set of constraint relations R' seeks C'. Based on the user u's knowledge features https://remittancesreview.com/article-detail/?id=1210 and goal features O^u, the set of conceptual sequences 8 from the set of topologically ordered sequences $\{C_1, C_2, \cdots C_k\}$ is filtered to the set of conceptual sequences $\{C_1', C_2', \cdots C_k'\}$ that the user may need to continue to learn, and for each of these C_i' is generated from the set of C_i sequences as follows:

$$C_i' = \{c_j \mid c_j \in C_i, (s_j < 3) \vee (s_j < 4) \wedge (o_j = 2) \vee (s_j < 45) \wedge (o_j = 3)\} \quad (10)$$

Where, for Concept c_j, if the assessment score is less than 3, or if the assessment score is between 3-4 and the learning goal is applied learning, or if the assessment score is between 4-5 and the learning goal is discovery learning, the concept is recommended to Concept Set C_i for continued learning.

For each sequence C_i in $\{C_1', C_2', \cdots C_k'\}$, take a substring C_u of a particular length and find the distance between the user's ability vector $B^u = (b_1^u, b_2^u, \cdots, b_p^u)$ based on that substring and the difficulty coefficient $Dif^u = (dif_1^u, dif_2^u, \cdots, dif_p^u)$ of that substring, and the substring with the most suitable distance is the target concept set. The absolute ability deviation is defined here to measure the deviation between the user's ability and the difficulty of the corresponding concept string, defined as follows:

$$ABE = \frac{1}{n}\sum_{t=1}^{\rho}(b_t^\alpha - dif_t^\alpha)^2 \quad (11)$$

Where, ABE the smaller the value of absolute ability deviation, the smaller the deviation of the user's ability from the difficulty of the concept substring, and the more adaptable the concept substring is to the user in theory.

Applying the angle cosine to calculate the distance between two vectors to generate an adapted initial course for the learner requires finding a sequence of concepts that is close to the minimum distance value. This suitable value is calculated according to the difference function to get a value between the maximum and minimum value, which is calculated as follows:

$$Dis = \cos(B^{\alpha}, dif^{\alpha}) = \frac{B^{\alpha} \cdot Dif^{\alpha}}{\left\|B^{\alpha}\right\| \times \left\|Dif^{\alpha}\right\|} = \frac{\sum_{t=1}^{\rho} b_t^{\alpha} dif_t^{\alpha}}{\sqrt{\sum_{t=1}^{\rho} b_t^{\alpha}} \sqrt{\sum_{t=1}^{\rho} dif_t^{\alpha}}} \quad (12)$$

A subset R^u of relations in relation set $RC^u = \{c_1^u, c_2^u, \cdots, c_p^u\}$ makes:

$$R^u = \{r \mid r = < c_j, c_k >, c_j, c_k \in C_u, r \in R'\} \quad (13)$$

The return value $KD' = \{C', R'\}$ of the correlation coefficient between the personality profile of user u and the learning object and concept is used as an input to the algorithm, i.e., the input value is the personalized historical knowledge course structure value.

Personalized History Course Learning Content Generation

History course content is composed of a set of learning objects that support conceptual learning, so this section utilizes the associative relationship between concepts and learning objects to further recommend a collection of learning objects that are compatible with KD and to generate structured history course content.

Based on the association matrix established between each learning object r_i in the collection of learning resources R and each concept c_j in the collection of concepts C, based on $C^u = \{c_1^u, c_2^u, \cdots, c_p^u\}$, an association matrix $R - C^u$ based on the association matrix between the learning resources R of the history course and the sequence of concepts C^u is generated, and then a vector of association relationships between a learning object r_i in the history course resources R and p concepts in the sequence of concepts C^u. Can be expressed as:

$$r_i^u = (v_{i1}^u, v_{i2}^u, \cdots, v_{ip}^u) \quad (14)$$

Based on the association relationship, the set of learning objects R supporting the set of concepts for point-in-time goals is generated, and the content of the historical course association between learning object r_i and concept set C^u is calculated as follows:

$$\eta_{ip}^u = \sum_{k=1}^{p} v_{ik}^u \quad (15)$$

$$\square' = \{r_i \mid r \in \square, r_i^u \in \square', \eta_{ip}^u \neq 0\} \quad (16)$$

Each learning object in the generated learning resource set R is used to support the learning of at least one of the concepts in the concept set C^u, but its difficulty and type are suitable for the learning ability and goal profile of a particular learner, which needs to be further filtered. The learning object resource set is generated based on the ability characteristics in the user's personality profile. Learning objects whose distance exceeds a certain threshold are further eliminated by finding the distance between the user's target feature vector and the learning object type feature vector. The final result is a history course learning content that is suitable for concept set C^u and also for a specific set of user learning objects.

Analysis of Educational Management and Innovation in the History Curriculum

In the experiment, a course in the subject of history in the undergraduate education in humanities at a teacher training university was selected as the experimental course. The instructor of this history course developed a lesson plan document according to the requirements, and at the same time, 100 students of undergraduate education in humanities were selected for online education, and 16 specialized instructors were given different lesson plans. The distance between the generated course and the co-occurring single course was fed back by the instructor, and the effectiveness of the algorithm of this paper was judged by analyzing the performance and achievement of the knowledge domain and learning resources.

Performance Analysis of History Course Knowledge Points

Among the performance evaluation index measures of recommendation algorithms, precision rate, recall rate and F1 value are the most widely used performance evaluation indexes. The key to the performance of recommendation algorithms lies in whether appropriate knowledge points of history courses are recommended to learners, so in the performance analysis of this section of the experiment, the performance differences between this paper's method and the comparison algorithms in terms of precision rate, recall rate, and F1 value are compared by constantly adjusting the number N of recommended knowledge points. Quantum algorithm, whale algorithm, and particle swarm algorithm are selected for the comparison method.

Precision and Recall Results

In this section, 10 different sizes of the number of history course knowledge points N are selected for performance comparison experiments to analyze how the performance of the algorithms varies with the number of recommended knowledge points N . The performance of this paper's algorithm and the comparison algorithm in terms of precision and recall is shown in Table 3. For different number of knowledge points recommended, the proposed algorithm performs better than the comparison algorithm in both precision rate and recall performance metrics. When the number of knowledge points in the history course is increased to 100, the precision rate is still as high as 88.2%, and the precision rate of the quantum algorithm is 54.1%. The whale algorithm has a precision rate of 58.7% and the particle swarm algorithm has a precision rate of 65.1%. Again the recall of this paper's method remains excellent with a recall of 60.9% and the quantum algorithm has a recall of 54.1%. Whale algorithm has a recall rate of 58.7% and particle swarm algorithm has a recall rate of 65.1%. It shows that the recommendation model proposed in this paper can combine the conceptual interaction reach of knowledge points, and the sequence learning mode of learners can better improve the performance evaluation index of recommendation algorithms.

In addition, Table 3 also shows that the precision rate of the proposed algorithm and the comparison algorithm gradually decreases and the recall rate gradually increases as the number of knowledge points N of the history course increases. This is due to the fact that the list of knowledge points that meets the needs of the target learner is limited, and as the number of recommended knowledge points increases, the list of recommended knowledge points that do not meet the needs of the learner increases, and thus the precision rate of the recommendation algorithms decreases gradually. The recall rate reflects the ratio of the list of knowledge points actually needed by the learner in the list of recommended knowledge points to the list of all knowledge points actually needed by the learner, while the number of all knowledge points actually needed by the learner is limited, and thus the ratio increases gradually with the increase in the number of recommended knowledge points.

Table 3 Performance in terms of accuracy and recall(%)

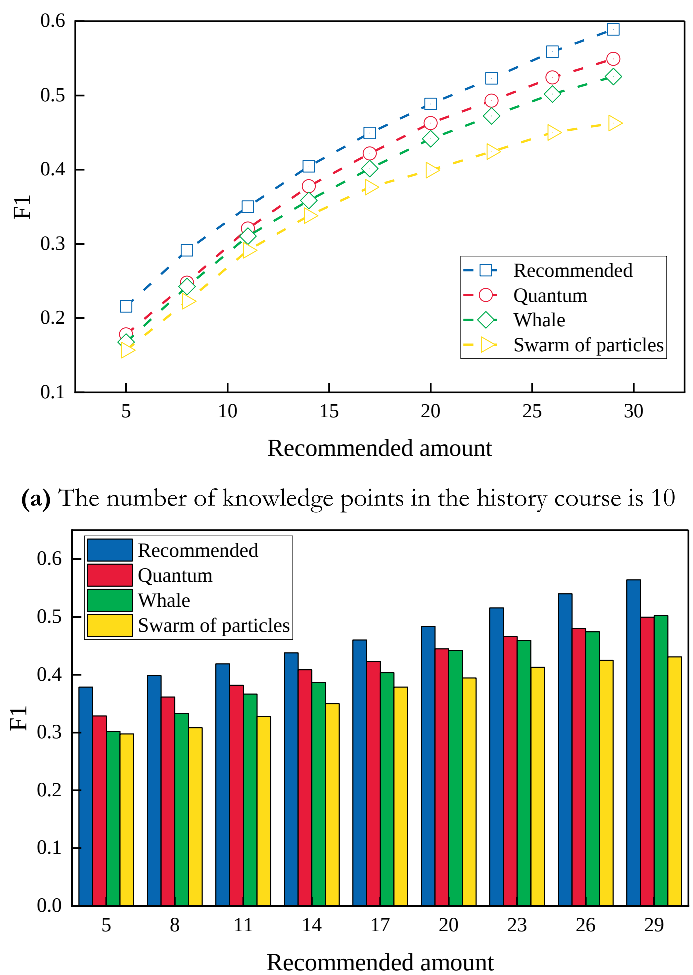
Knowledge points of N	**Proposed method**		**Quantum algorithm**		**Whale algorithm**		**Particle swarm algorithm**	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
10	97.1	35.8	65	11.3	63.2	9.8	73.7	8.7
20	96.9	39.3	63.3	14.8	62.9	15.3	72.8	11.3
30	96.6	45.6	62.9	21.5	62.2	18.8	71.2	15.8
40	95.9	47.3	62.1	26.6	62	20.1	70	20.6
50	95.2	48.2	61.9	31.8	61.5	23.4	69.5	26.4
60	94.5	49.5	61.3	33.2	61.2	26.7	68.2	29.7
70	92.9	54.7	60.9	34.8	60.9	28.9	67.9	34.5
80	92.1	58.7	59.6	36.4	60.1	34.6	66.1	39.6
90	89.6	59.1	57.2	36.9	59.1	35.7	65.8	39.9
100	88.2	60.9	54.1	42.1	58.7	36.3	65.1	41.2

Results of F1 value analysis

The above analysis shows that the growth trend of precision rate and recall rate of recommendation algorithms are negatively correlated. Therefore, this paper adopts the F1 value to comprehensively compare the precision rate and recall rate of recommendation algorithms. Figure 4 shows the change of F1 value with the number of recommended knowledge points.

Figure 4(a) shows the F1 value when the number of knowledge points of the history course is 10, and the proposed algorithm outperforms other methods in the F1 value for different numbers of recommended knowledge points. The F1 value of this paper's method is 60% when the number of recommendations is 29, which improves the F1 value of this paper's method by an average of 5.67% and 3.41% compared to other methods. In addition, all the F1 values increase gradually with the increase of the number of recommended knowledge points, indicating that the more the number of recommended knowledge points in a certain range, the higher the F1 value of the recommendation algorithm, while too many recommended knowledge points will make the overall performance of the algorithm no longer have a significant increase in the growth trend (Todorova, 2019).

Figure 4(b) shows the F1 value when the number of knowledge points in the history course is 100, the F1 value of this paper's method is 58.9% when the number of recommendations is 29, the F1 value of the quantum algorithm is 45.4%, the F1 value of the whale algorithm is 46.7%, and the F1 value of the particle swarm algorithm is 41.9%. It shows that the method in this paper has excellent reconciled average values and can provide personalized learning materials and learning paths for each student. This is mainly due to the fact that the method in this paper utilizes the absolute ability bias at the beginning of the learning process, calculates the adaptability of the conceptual substring to the user, and uses the user's personality characteristics and the correlation coefficient between the learning object and the concepts as the value of the course structure, so as to generate history syllabi for the learners with different abilities that are adapted to their level of ability.



(a) The number of knowledge points in the history course is 10

(b) The number of knowledge points in the history course is 100

Figure 4 F1 value under the number of recommended knowledge points for history courses

Analysis of History Course Achievement Results

This subsection of the experiment of the ability to validate the method of this paper similar to the innovation of the course through the learning behavior situation of 100 students. In the college history course units 1-8 units in the achievement test, Figure 5 shows the college history course student achievement, it can be seen in the history course unit 1, 92% of the students in history scores of 80 points or more, 5% of the students in history scores between 60-80 points, 3% of the students in history scores of less than 60, the history course units 1-8 units of the achievement of 80 points or more accounted for the largest percentage This paper illustrates that the methodology of this paper helps students to better understand and master their historical knowledge and improve their learning outcomes and academic performance through the implementation of personalized college and university history curriculum generation.

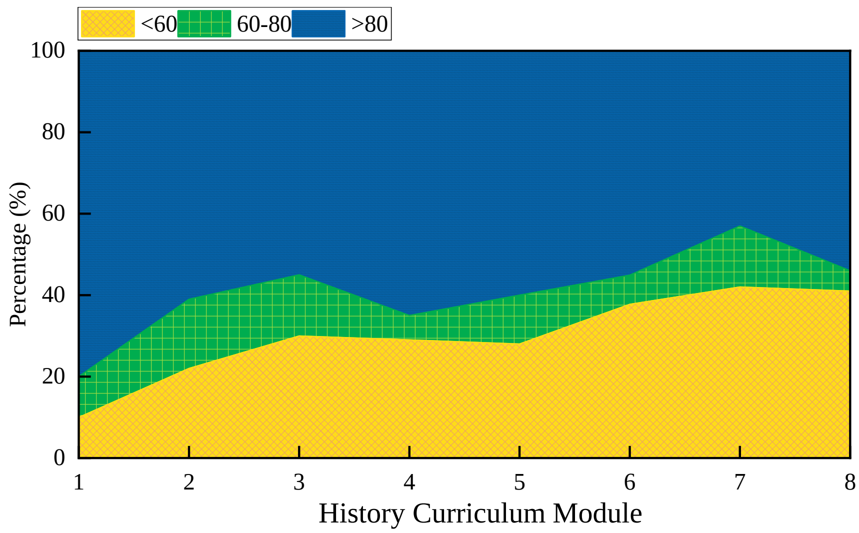


Figure 5 History Course Score Results

Conclusion

In order to improve the educational management of history courses in colleges and universities, an educational model of innovative thinking is proposed. Firstly, a directed acyclic graph of constraint relations is established to determine the structure of history courses in colleges and universities. Collect a series of data on learners' learning behaviors and extract learning personality characteristics. Combining the characteristics of the collection of learning objects and establishing the correlation between user needs and learning objects, applying the angle cosine to calculate the value of the history knowledge course structure to determine the students' learning interests and needs. The correlation matrix between history course learning resources and concept sequences is used to generate personalized history course learning content. The results show that the precision rate is as high as 97.1% and the recall rate is 60.9% among 10 different sizes of history course knowledge points. Comparing with other methods, the F1 value of this paper's method is 60% when the number of history course knowledge points is 10, and 58.9% when the number of knowledge points is 100. And the comprehensive performance of the history course is excellent, in the first history unit, 92% of the students' history scores are above 80 points, which proves that this paper explores the ability to adapt to the management strategy and development direction of the digital era, and helps students to better understand and master the historical knowledge, and improves the learning effect and learning performance through the implementation of personalized course generation. This will provide a useful reference and reference for the innovative development of history course education in colleges and universities.

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