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Mathematical Modeling Research on Optimization of Ideological and Political Education Teaching Mode and Personalized Learning Path Based on Artificial Intelligence

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Abstract The deepening of the integration of artificial intelligence technology and the field of education has injected new vitality into the optimization of the ideological and political education model. This paper focuses on the optimization of the ideological and political teaching mode and the construction of its personalized learning path, and analyzes three important problems encountered in the construction of the personalized learning path for ideological and political education. Subsequently, it describes the representation of seven learner characteristic parameters as a reference for the representation of the learner characteristic data set in the personalized learning path. After completing the preparation and input of learner characteristic data, the improved genetic algorithm is applied to construct the personalized learning path model under the Civic Education Mode. With the assistance of the designed personalized learning path model, students' knowledge mastery rate can be increased by up to 35.18%. With the support of artificial intelligence, the personalized learning path model of Civic and Political Education can effectively recommend learning resources and provide learning assistance according to the individual situation of different learners.

Index Terms artificial intelligence, civic education, personalized learning path, improved genetic algorithm

I. Introduction

Artificial intelligence (AI) is an important driving force leading a new round of technological revolution and industrial change, which is profoundly changing people's way of production, living, and learning, and promoting human society to usher in the intelligent era of human-computer collaboration, cross-border integration, and co-creative sharing [1]-[3]. In the survey of literature [4], more than 80% of students support independent learning strategies, virtual teachers, and intelligent assistants implemented with artificial intelligence. The new generation of information technology represented by artificial intelligence is transforming from an exogenous variable affecting education to an endogenous force leading comprehensive, systematic, and deep-level changes in education [5].

Ideological and political education is the key education for the implementation of moral education. However, in ideological and political education, the collectivity, singularity and solidification of the teaching mode and the backwardness of teaching evaluation have led to a serious lack of the level of personalization of education and poor teaching results. In the context of the big era and pattern of artificial intelligence, ideological and political education to update the concept, build a new model, reshape the teaching form has become a realistic requirement and an inevitable choice, to promote the intelligence, precision and personalization of the teaching of the ideological and political class, to build a precise teaching mode, and to explore the practice strategy of precise teaching, in order to better achieve the goal of educating people, which is an important topic of the current ideological and political reform and innovation [6], [7].

In recent years, the deep integration of artificial intelligence technology and ideological and political teaching has continuously promoted the breakthrough of ideological and political education from theory to practice, and promoted educational reform and innovation. The theory of the current ideological and political education curriculum is constantly maturing, and the constant updating of intelligent information processing technology makes modern education characterized by diversified information, diversified educational subjects, and hierarchical educational objects. From the data itself to find the source of innovation drive, construct the ideological and political teaching model, intelligent, accurate teaching to promote the comprehensive and free development of students, to realize the intelligent teaching and learning of the educational process, and to enhance the effectiveness of education, is the inevitable choice for the reform and development of ideological and political education in the era of intelligence and innovation.

In education, the application scenarios of artificial intelligence include, but are not limited to, the reform of teaching mode, personalized teaching design, personalized learning strategies. Literature [8] used artificial intelligence to construct a model of intelligent network interaction system, which was used for teaching and learning by analyzing students' ability level, managing students in a hierarchical manner, recommending precise educational resources to students of different ability levels, as well as predicting the learning effect of students' online platform. Literature [9] developed an AI-supported “Emergency Distance Learning” teaching model to cope with educational problems in emergencies such as epidemics and to realize normal teaching and learning. Literature [10] mentions that AI can optimize blended teaching and learning beyond the basic physical space by enhancing the effectiveness of teacher-student interactions, fostering students' personalized development, and evaluating students' literacy. Literature [11] constructed a dynamic model and a dynamic personalized learning path resource recommendation algorithm for incremental learning based on AI, where the former simulates the students' learning process and the latter optimizes the design of students' personalized learning paths. Literature [12], by analyzing literature data from different countries, concluded that artificial intelligence has strengthened the teaching content, personalized learning path design based on students' individual needs, habits, and abilities, and at the same time tapped into the learning difficulties to continuously optimize the learning effect. Literature [13] proposes a personalized learning strategy and environment for AI in conjunction with agile teaching strategies, which is also effective for collaborative learning, revolutionizing traditional teaching methods and assisting in the adaptation of students to flexible and dynamic environments. According to the reform of teaching mode and personalized learning planning of AI in education, it provides a reference for the optimization of teaching mode and personalized learning path planning of Civic and Political Education under AI.

This paper firstly elaborates the construction idea of personalized learning path for Civic and Political Education from the perspectives of data privacy and security, data analysis and application, and personalized learning resources development issues. Then, it describes the representation of seven learner characteristic parameters in turn, and completes the representation of learner learning characteristics and inputs in the personalized learning path system. Then we design the two stages and framework for constructing personalized learning path, introduce the improved genetic algorithm, and complete the establishment of personalized learning path for Civic and Political Education. Finally, we design a comparison experiment with similar algorithms in terms of the order of recommended knowledge points and the improvement of learning efficiency to test the feasibility and reliability of the path model.

II. The Need for Building Personalized Learning Paths in Civic Education

II. A. Privacy and security of data collection and processing

The collection and processing of student data becomes particularly critical when implementing the design of personalized learning pathways for Civic Education based on big data. This type of data generally contains students' personal information, learning behaviors, grades, and so on, and its sensitivity and importance require educational institutions to manage it with a high sense of responsibility. Privacy and data security issues are the first challenge in this process. Inappropriate data collection and processing can not only infringe on students' privacy, but also cause serious consequences such as data leakage and misuse, thus jeopardizing the interests of students and educational institutions. Therefore, ensuring data security and protecting student privacy is an important step that cannot be ignored when building on big data applications.

II. B. Accuracy of data analysis and application

Whether the data analysis is accurate or not is the key element for the success of personalized learning path design. How to accurately interpret and use the massive and complicated student data in the process of personalized teaching in Civics education has become a huge problem. The quality of data and the scientific method of analysis are directly related to the reliability and validity of the final analysis results. Inaccurate data analysis will lead to teaching decision-making errors, affecting teaching effectiveness and student learning outcomes. Therefore, it is of great significance to improve the accuracy of data analysis and choose appropriate data processing tools and methods to achieve efficient personalized learning path design.

II. C. Development and Integration of Personalized Learning Resources

The realization of personalized learning paths depends on rich and colorful learning resources. However, in practice, the lack of high-quality personalized learning resources and inadequate resource integration mechanisms have become constraints to the design and implementation of personalized learning paths. The development of learning resources requires huge investment of time, money and expertise, and effective resource integration requires good collaboration among educational institutions and technology providers. The lack of efficient resource development and integration strategies will prevent students from meeting their individual learning needs, thus affecting the effectiveness of personalized learning pathways in reality.

III. Construction of Personalized Learning Path Model for Civic Education

III. A. Learner Characterization Parameter Representation

(1) Demographic features

Given a set of demographic features $DC=\{DC_1,DC_2,\cdots,DC_n\}$, n denotes the number of learners, and $DC_j=\{g_{1j},g_{2j},g_{3j},e_{1j},e_{2j},e_{3j},d_{1j},d_{2j}\}$ denotes the basic characteristics of the j th learner, where the stage of age and education are denoted by g_i and e_i, respectively, and take the value of 1 or 0, with 1 denoting in the interval, and 0 denoting not in the interval , $i=\{1,2,3\}$. Use d_k to denote gender, $k=\{1,2\}$, d_1 to denote male, d_2 to denote female, and $d_i=\{1,0\}$ to denote yes and no, respectively.

(2) Learning Motivation

Given the set of learning motives $LM=\{LM_1,LM_2,\cdots,LM_n\}$, n denotes the number of learners, $LM_j=\{lm_{1j},lm_{2j},lm_{3j},lm_{4j},lm_{5j},lm_{6j},lm_{7j},lm_{8j},lm_{9j}\}$ denote the motivation of the j th learner, where $lm_{ij}=\{1,0\}$, denoting yes and no, respectively, and $i=\{1,2,3,4,5,6,7,8,9\}$, corresponding to the 9 types of learning motives, respectively.

(3) Learning styles

Given a set of learning styles $LS=\{LS_1,LS_2,\cdots,LS_n\}$, n denotes the number of learners, $LS_j=\{ls_{1j},ls_{2j},ls_{3j},ls_{4j},ls_{5j},ls_{6j},ls_{7j},ls_{8j}\}$ is a representation of the learning style characteristics of the j th learner, where $ls_{ij}=\{1,0\}$, which denotes yes or no respectively , $i=\{1,2,3,4,5,6,7,8\}$, corresponding to the 8 learning styles, respectively.

(4) Information Literacy

Given the information literacy set $FL=\{FL_1,FL_2,\cdots,FL_n\}$, n denotes the number of learners, $FL_j=\{fl_{1j},fl_{2j},fl_{3j},fl_{4j},fl_{5j},fl_{6j},fl_{7j},fl_{8j}\}$ denotes the information literacy of the j th learner, where $fl_{ij}=\{1,0\}$, which denotes yes or no respectively, and $i=\{1,2,3,4,5,6,7,8\}$, which corresponds to the 8 types of information literacy, respectively.

(5) Cognitive Characteristics

1) Cognitive level

Given the set of cognitive levels $KL=\{KL_1,KL,\cdots,KL_n\}$, n denotes the number of learners, $KL_j=\{(k_1,l_1),(k_2,l_2),\cdots,(k_m,l_m)\}$, denotes the cognitive level of the j th learner, k_i denotes the i th knowledge point, m denotes the total number of knowledge points, l_i denotes the category of the 7 cognitive levels, $l_i=\{0,1,2,3,4,5,6\}$.

2) Cognitive Abilities

Given a set of cognitive styles $CA=\{CA_1,CA_2,\cdots,CA_n\}$, n denotes the number of learners, $CA_j=\{ca_{1j},ca_{2j},ca_{3j},ca_{4j},ca_{5j},ca_{6j},ca_{7j},ca_{8j}\}$ denotes the cognitive ability of the j th learner, where $cs_{ij}\in(0,1)$, i denotes the cognitive ability of the number of categories, $i=\{1,2,3,4,5,6,7,8\}$, which corresponds to each of the 8 cognitive abilities.

3) Cognitive Style

Given the set of cognitive styles $CS=\{CS_1,CS_2,\cdots,CS_n\}$, where n denotes the number of learners, $CS_j=\{cs_{1j},cs_{2j},cs_{3j},cs_{4j},cs_{5j}\}$ denotes the cognitive style of the j th learner, where $cs_{ij}\in(0,1)$, and i denotes the number of categories of cognitive styles, $i=\{1,2,3,4,5,6\}$, correspond to the 6 cognitive styles respectively.

(6) Learning Preferences

Given the set of learning preferences $LP=\{LP_1,LP_2,\cdots,LP_n\}$, n denotes the number of learners, $LP_j=\{Pr_{1j},Pr_{2j},Pr_{3j},Pr_{4j},Pt_{1j},Pt_{2j},Pt_{3j},Pt_{4j},Pt_{5j},Pl_{1j},Pl_{2j},Pl_{3j},Ps_{1j},Ps_{2j},Ps_{3j}\}$ denotes the learning preference of the j th learner, where Pr_{ij} denotes the j th learner's preference for resources: course text material, course video material, course audio material, and post-course exercises. Pt_{kj} represents the j th learner's preference for study time: morning, am, noon, pm, evening, night. Pl_{hj} represents study duration preference: 0-20 minutes, 21-40 minutes, 41-60 minutes. Ps_{wj} indicates learning strategy preference: instructional, inquiry, cooperative.

where $Pr_{ij} \in (0,1)$, $Pt_{kj} \in (0,1)$, $Pl_{hj} \in (0,1)$, $Ps_{wj} = \{1,0\}$, indicating yes or no. i denotes the number of preference types of resources, $i = \{1,2,3,4\}$, corresponding to each of the 4 resources. k denotes the number of preference types for learning duration, $k = \{1,2,3,4,5\}$, corresponding to 5 time periods, respectively. h denotes the number of preference types for learning durations, $h = \{1,2,3\}$, corresponding to 3 types of learning durations, respectively. w denotes the number of preference types of learning strategies, $i = \{1,2,3,4\}$, corresponding to 4 kinds of resources, respectively.

(7) Learning Attitude

The given set $LA = \{LA, LA_2, \cdots, LA_n\}$ denotes the cognitive styles of n learners, $LA_j = \{la_{1j}, la_{2j}, la_{3j}\}$ denotes the learning attitude of the j th learner, where $la_{ij}d_i = \{1,0\}$, denotes yes or no, respectively, and i denotes the number of categories of the learning attitudes, $i = \{1,2,3\}$, which corresponds to the three kinds of attitudes, respectively.

III. B. Building the framework

The essence of personalized learning path construction is to match the fitness between learner characteristics and knowledge point characteristics, and select the learning sequence that best meets the learning needs and characteristics of individual learners as a learning path to help them complete their learning tasks and improve their learning efficiency.

Regarding the personalized learning path construction framework, it is realized in two stages. The first stage utilizes the knowledge graph to generate a generic learning path. The second stage takes the knowledge point sequence of the generic learning path as the basis, and combines the relevant attributes in the learner model and the knowledge point model as inputs, applies the improved genetic algorithm, and the final output is to generate a personalized learning path suitable for the learner's characteristics, and the complete personalized learning path implementation process is shown in Figure 1.

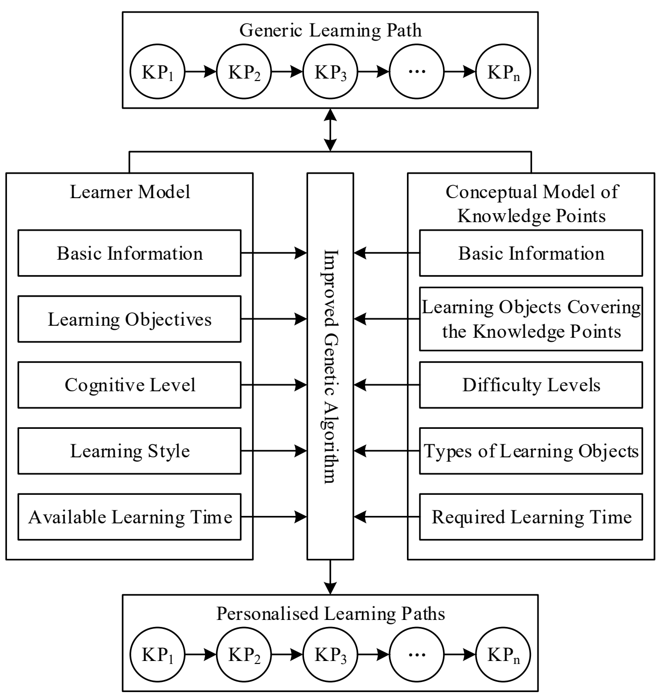


Figure 1: A framework for constructing personalized learning paths

III. C. Improved genetic algorithm

Based on the personalized learning parameters and related metadata, we construct the learner model and knowledge point model, and use them to design the personalized learning path construction framework, and use the improved genetic algorithm to construct the personalized learning path to meet the learners' learning needs. The main implementation steps of the improved genetic algorithm to construct personalized learning path are as follows.

(1) Parameter encoding: the use of genetic algorithms to solve the problem of personalized learning path construction needs to encode the candidate solution set of the problem as a set of chromosomes, and the quality of the encoding will directly affect the effect of path construction. According to the prerequisites such as the learner's cognitive level, available learning time, etc., n knowledge points are selected in the sequence of generic learning paths, denoted as $CS=(C_1,C_2,\cdots,C_n)$. Let each concept C_i in CS include m types of learning objects, but only one learning object can be used to construct a learning path, and the parameters can be encoded accordingly. An individual presented as R_{ij} is denoted as the i th type of learning object in the j th knowledge point. In the previous design of parameter encoding, considering that there are n knowledge points in CS and each knowledge point C_i contains m types of learning objects, the scale of encoding will be the size of the number of $n*m$, but this greatly increases the algorithm computational complexity. In this study, the selection of learning objects is determined by learner characteristics. In the encoding process with reference to specific types of learning objects to complete the final form of encoding, not only reduces the complexity of the algorithm, but also improves the efficiency of the algorithm execution, the encoding process is shown in Figure 2.

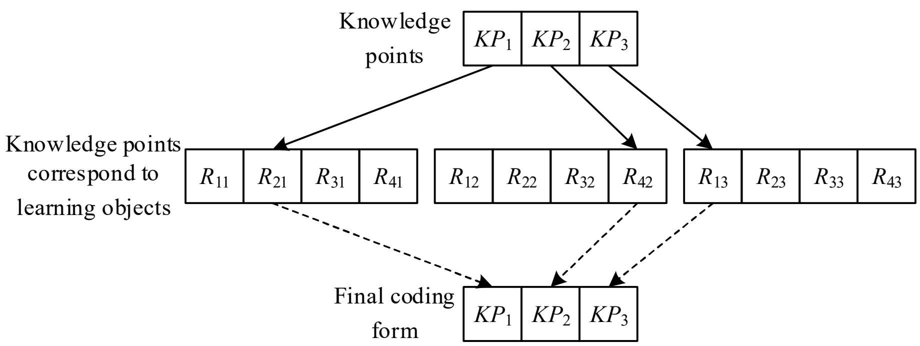


Figure 2: Parameter coding

(2) Initialization population: The genetic algorithm starts by generating an initial population, which consists of a certain number of feasible candidate solutions, and the number of candidate solutions represents the population size, which remains unchanged during the GA process. The initial population is generated in a randomized way to ensure the diversity of the population and to improve the convergence to the optimal solution. In this study, the initial population size is jointly determined by the generic learning path, learner characteristics and knowledge point characteristics.

(3) Fitness evaluation: after the initialization is completed, the fitness function evaluates the fitness value of each individual to determine the fitness between the learning object and the learner's characteristics, and selects the better individual as the parent generation for reproduction. The learning path personalization generation problem is modeled as an objective optimization problem using learner features and knowledge point features as constraints. The learner feature is denoted as $L_{pr}=(LT_m,LS_m,AL_m,AT_m)$, the knowledge point feature is denoted as $KP_{pr}=(MC_n,MS_n,DL_n,MT_n)$, and the fitness function is shown in equation (1).

$$f=\sum_{i=1}^{4}\left(wi\times f_i\left(L_{pr},KP_{pr}\right)\right) \tag{1}$$

where: wi denotes the weight of the fitness function, which is applicable to adjust the proportion of f_i, and the importance of the fitness function can be determined by adjusting the corresponding weights, e.g., $(w1,w2,w1,w2)=(0.25,0.25,0.25,0.25,0.25)$, which means that $f1$, $f2$, $f3$ and $f4$ have the same weight. f_i denotes the number of participant adaptations between learner features and knowledge point features.

The smaller the value of the fitness function f, the more the constructed learning paths are represented to fit the learner characteristics. The four objectives considered in the fitness function are $f1$, $f2$, $f3$ and $f4$.

$f1$ is the average difference between the knowledge points (MC_n) covered by the learning object in the constituent learning path and the current learner's learning objectives (LT_m), calculated as in equation (2).

$$f1 = \sum_{i=1}^{K} |MC_n - LT_m| / K \tag{2}$$

where: K is the number of selected knowledge points and also the number of learning objects.

$f2$ is the average difference between the type (MS_n) of the learning objects in the constituent learning paths and the current learner's learning style (LS_m), which is computed as in Equation (3).

$$f2 = \sum_{i=1}^{K} |MS_n - LS_m| / K \tag{3}$$

$f3$ is the average difference between the difficulty level (DL_n) of the knowledge points in the constituent learning path and the cognitive level of the current learner (AL_m), calculated as in equation (4).

$$f3 = \sum_{i=1}^{K} |DL_n - AL_m| / K \tag{4}$$

$f4$ is the average difference between the learning time (MT_n) required for the knowledge points in the constituent learning paths and the learning time (AT_m) available to the current learner, computed as in Eq. (5).

$$f4 = \max\left(0, \sum_{i=1}^{K} MT_n - AT_m\right) \tag{5}$$

After encoding, initialization and selection of the appropriate fitness function, the genetic manipulation operator is also used to iteratively generate high-quality individuals to form new offspring individuals.

IV. Evaluation of the application of the personalized learning path model

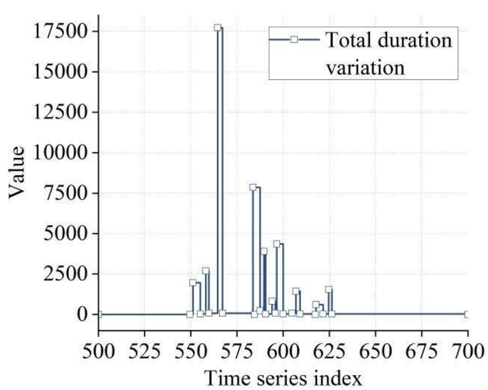
This chapter takes E learners as the research object and carries out their multidimensional time series characteristics and original knowledge point mastery description on MoocCubeX dataset. Then, the Civic Education Personalized Learning Path is used to determine the fusion factor of knowledge semantic similarity and scoring semantic similarity, and compare the performance of the proposed Civic Education Personalized Learning Path model with similar model algorithms in terms of the order degree of the recommended knowledge points and the students' learning efficiency.

IV. A. Preparation of the study

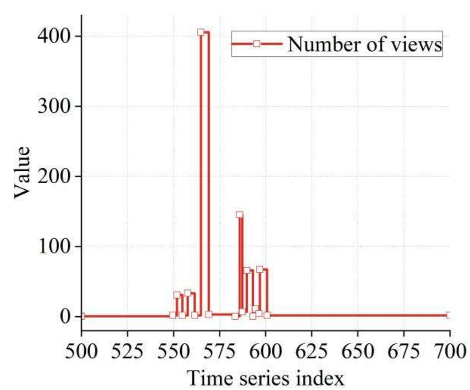
The Civics Classroom open source dataset MoocCubeX is chosen as the original dataset for this experiment, and this experiment focuses on the analysis of learners' video viewing behavior in the dataset.

IV. A. 1) Multidimensional Time Series Characterization of Learners

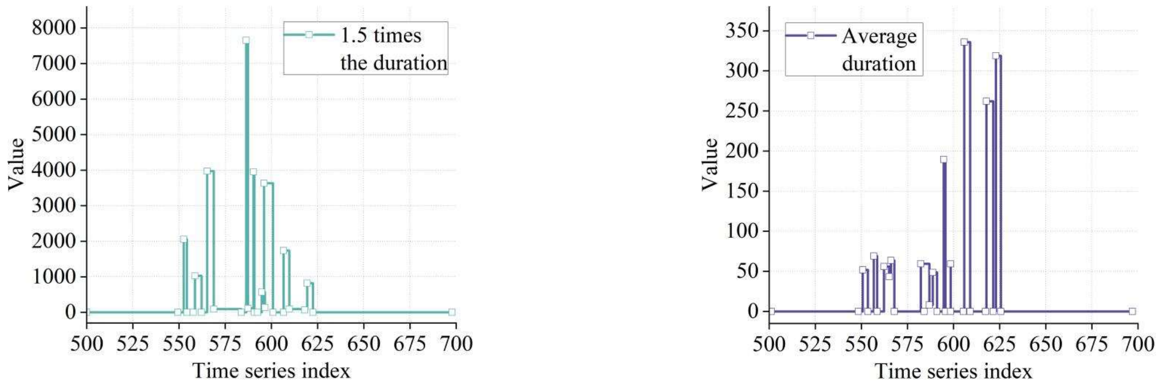
The reconstructed multidimensional time series characteristics of Learner E, for example, are shown in Figure 3.



(a) Total duration variation



(b) Number of views



(c) 1.5 times the duration

(d) Average duration

Figure 3: The time series characteristics of some learners

At this point, the original construction of the learners' time-series characteristics was completed, and some of the time-series data are shown in Table 1.

Table 1: Partial time series characteristic data

Uid	1	2	3	4	5	6	7	8	9	10
Time	558	559	560	561	562	563	564	565	566	567
Sum	2134	3072	0	0	0	0	3030	5512.6	18113.26	12564
Count	34	41	0	0	0	0	50	94	424	181
1.0	0	0	0	0	0	0	0	0	0	0
1.25	0	0	0	0	0	0	0	54.6	37.6	0
1.5	66	1064.6	0	0	0	0	1103	3036.6	4122.26	2010
2.0	2069	2006.6	0	0	0	0	1928	2421.6	4122.26	2010
Avg	64.637	76.776	0	0	0	0	61.817	59.275	42.822	69.795
Max	171	381	0	0	0	0	263	270	320.6	401
Min	0	0	0	0	0	0	0	0	0	0
Am	2134	3072	0	0	0	0	3030	3323.6	9005	9062
Pm	0	0	0	0	0	0	0	2188	9109.26	3503

The constructed dataset is manually annotated, and the analysis of the data can find that the learning data of most learners in the time domain is very sparse, so the data are classified from two dimensions in the multi-classification annotation, which are divided into three categories from the time domain: "long ago (360 days ago)", "not long ago (90 days ago)", and "recently (within 90 days)", and "less active", "relatively active" and "very active" in terms of activity, with a total of 27 categories to label the data.

IV. A. 2) Degree of students' mastery of knowledge points

In order to deeply analyze the dynamic changes of students' knowledge status in the learning process, the interaction sequence of students completing 20 consecutive practice questions on the MoocCubeX dataset is shown in Fig. 4 through the visualization technology, with the 20 practice questions numbered from 1 to 20. The Z-axis value of the figure indicates the expected degree of knowledge mastery, and at the same time intuitively reflects the degree of mastery of students on the various knowledge points through the color shades. The knowledge points involved include “life values”, “basic connotation of patriotism” and “socialist thinking on the rule of law”.

From the figure, it can be seen that when students make mistakes on the knowledge point Skill8, 13-14 (Life Values), the color of the corresponding knowledge status becomes lighter, and the highest mastery level is only 0.2. This indicates that students' mastery level on this knowledge point has decreased. Due to the interconnectedness of knowledge points, students' correct responses on one knowledge point will lead to an increase in the mastery of other related knowledge points. This phenomenon suggests that practicing for a particular concept not only strengthens the understanding of that concept, but also positively affects the knowledge status of related concepts.

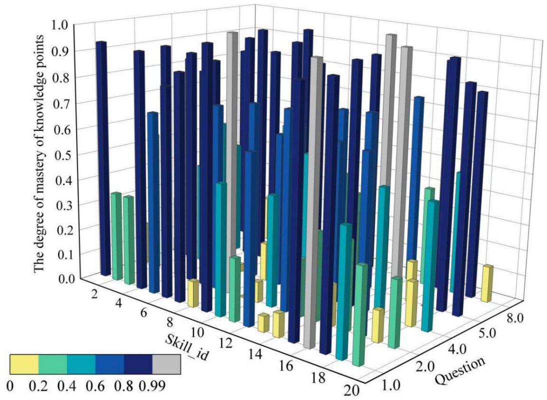
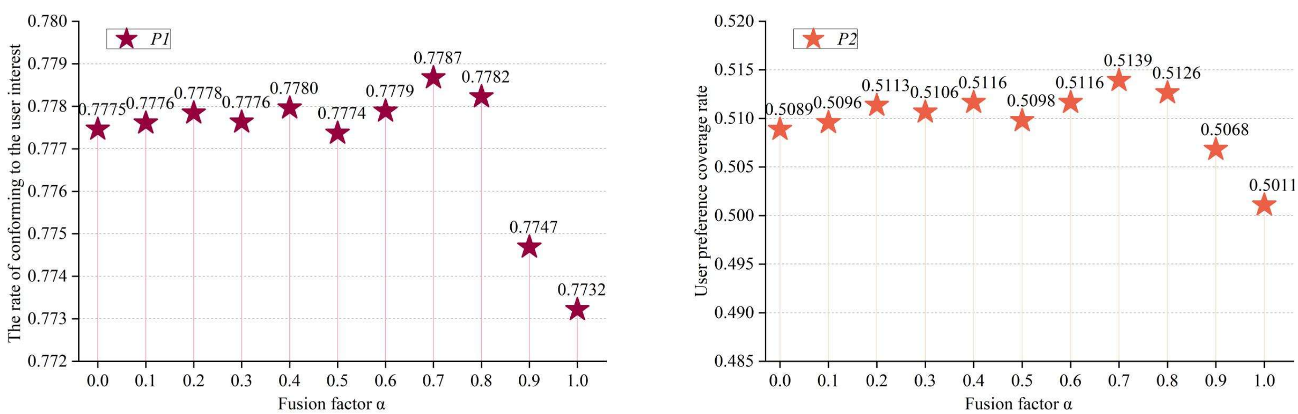


Figure 4: The students' mastery of knowledge points

IV. B. Experimental results

IV. B. 1) Fusion Factor Determination

This subsection performs the determination of the fusion factor of semantic similarity and scoring similarity of knowledge points. In the fusion factor α ($0 \le \alpha \le 1$), α is the coefficient of semantic similarity and 1 - α is the coefficient of scoring similarity, and the sum of the two is the final generated knowledge point similarity. The fusion factor α is selected as 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0 for the test. Since the value of the fusion factor directly affects the quality of the similarity of the final recommended knowledge points, which in turn affects whether the recommended results are in line with user preferences. Therefore, using the personalized learning path designed in this paper at each value of the fusion factor, score prediction and generate recommendation results, the statistical recommendation of the rate of conformity with user interest P1 is shown in Fig. 5(a) and the user preference coverage P2 is shown in Fig. 5(b). Where the horizontal axis is the value of the fusion factor α.



(a) P1 Value

(b) P2 Value

Figure 5: It conforms to the user interest rate and the coverage rate of user preferences

Compliance with the overall trend of user interest rate P1 and user preference coverage rate P2 is basically similar, both of which are first rising and then falling: when α = 0, the personalized learning path only considers the user rating similarity, at this time, P1 is only 77.75%, P2 is only 50.89%, and both of them take the value of unsatisfactory. When the value of α gradually increases, the proportion of semantic similarity gradually increases, and P1 and P2 show a zigzag upward trend. Until α=0.7, both indicators reach the maximum value, at which time P1 is 77.87% and P2 is 51.39%. After that, continue to increase the value of α, the values of P1 and P2 decrease rapidly. When α = 1.0, the personalized learning path only considers semantic similarity, at which time P1 is only 77.32% and P2 is only 50.11%.

To summarize, only consider the scoring similarity or semantic similarity, can not get better recommendation results, need to fuse the two, when the fusion factor α value of 0.7, can get the most accurate knowledge point similarity, to achieve the optimal compliance with the user's interest rate P1 and the user preference coverage rate

P2. Therefore, in the following two comparative experiments, this paper's learning path recommending algorithm's fusion factor value are 0.7.

IV. B. 2) Comparison of the orderliness of knowledge points in the pathway

This subsection performs a comparison of the knowledge point orderliness of the learning paths recommended by (B3) the model algorithm of this paper, (B2) the Trans-CF algorithm, and (B1) the Ontology-CF algorithm. The path knowledge point order degree is the probability that two neighboring knowledge points in the recommended learning path have a prior succession relationship. The maximum number of successive knowledge points in the learning path max_pre is selected as an important parameter that affects the performance of the model algorithm in this paper. max_pre is the maximum number of successive knowledge points queried when recommending a path for the knowledge points in the initial set of knowledge points to be recommended.

(B2) Trans-CF algorithm and (B1) Ontology-CF algorithm do not take into account the successive relationship of knowledge points, so the value of max_pre will not have an impact on their recommendation results. When max_pre is 2, 4, 6, 8 and 10, respectively, we calculate the knowledge point order degree of the recommended path of (B3) model algorithm in this paper, and compare the results with the knowledge point order degree of the recommended path of (B2) Trans-CF algorithm and (B1) Ontology-CF algorithm in Fig. 6.

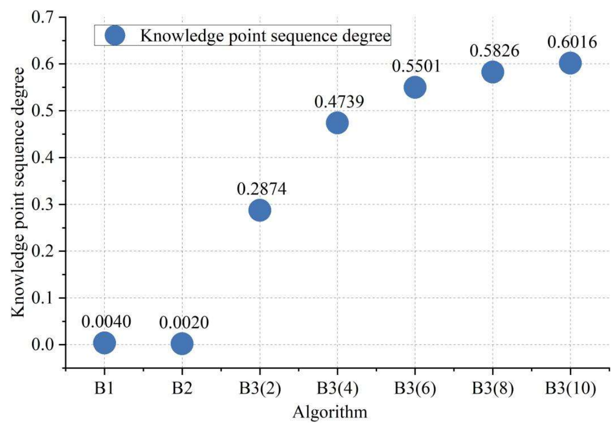


Figure 6: A comparative experiment on the sequence degree of knowledge points

From Fig:

(1) (B2) Trans-CF algorithm and (B1) Ontology-CF algorithm recommended learning path order degree is almost zero, the knowledge is more cluttered, no rules to follow, is not conducive to the learner's systematic learning. (B3) The learning path order degree recommended by the model algorithm in this paper is 0.2500 and above regardless of the value of max_pre, which is significantly higher than that of (B2)Trans-CF algorithm and (B1)Ontology-CF algorithm, which can better enhance the learning experience, user satisfaction and the interpretability of the learning path.

(2) (B3) The learning path order degree recommended by the model algorithm in this paper shows a monotonically increasing trend with the increase of max_pre, the maximum number of prior knowledge points. When max_pre=2, the learning path order degree is 0.2874, and then monotonically increasing, the growth rate is gradually slow, when max_pre=10, the learning path order degree reaches 0.6016, at this time, the probability of the learning path adjacent to the two knowledge points with the successive successor relationship is maximum. If max_pre is too small, it will lead to the path of knowledge points in the order of degree is too small, the learner learning the current personalized weak knowledge points, failed to solidly grasp the successor knowledge points, so that the learner's basic knowledge is not solid, is not conducive to the learner's subsequent learning. If max_pre is too large, it will make learners spend too much time on a weak knowledge point, constantly learning the current weak knowledge point of the successor knowledge point, thus ignoring the other weak knowledge points of the current course, reducing learning efficiency. Therefore, this paper selected max_pre=4 for the follow-up experiment, which ensures a solid mastery of the current weak knowledge points, without delaying the learning of the remaining weak knowledge points.

IV. B. 3) Comparative Learning Efficiency Experiment

This section compares the learning efficiency of the (B3) model algorithm of this paper, (B2) Trans-CF algorithm, and (B1) Ontology-CF algorithm, and defines the learning efficiency as the improvement of the degree of mastery of the knowledge points in the same time. After sorting all knowledge point learning records of learners for a course in chronological order, K is set as the current learning progress of learners, i.e., the proportion of knowledge point learning records currently completed. K is selected to be equal to 50, 60, 70, 80, 90 for comparison experiments. Indicates that when the learner completes 50%, 60%, 70%, 80%, 90% of all learning records of a certain course, the statistics of the mean value of the mastery of the knowledge points of this course without follow-up learning, as well as after learning according to the paths recommended by (B3) this paper's modeling algorithm, after learning according to the paths recommended by (B2) the Trans-CF algorithm, after learning according to the paths recommended by (B1) the Ontology-CF algorithm recommended path after learning, and after learning according to the learner's own path, the mean value of the mastery of all knowledge points of this course obtained.

Figure 7 shows the results of finding the mean value of students' knowledge point mastery improvement after all the courses in the dataset are recommended, the X-axis indicates the value of the current progress K of the completed learning record, and the Z-axis indicates the knowledge point mastery before and after learning according to the various paths. (B4) represents the average knowledge point mastery level of this course without subsequent learning. (B5) denotes the average knowledge point mastery level of this course after learning according to the remaining paths of the original learning record without any recommended results by the learner.

Comparing (B4) with the remaining four curves respectively, it can be seen that all four learning paths have improved the mastery of knowledge points, and as the value of K increases, the remaining learning time becomes less, which leads to a gradual decrease in the improvement of the mastery of knowledge points in the four recommended paths. Comparing (B1), (B2), (B3) and (B5), respectively, it can be seen that the enhancement of knowledge point mastery by (B3) the modeling algorithm in this paper, (B2) Trans-CF algorithm and (B1) Ontology-CF algorithm is better than that of the learner's original learning path, which indicates that the above three learning path recommendation algorithms can enhance the learners' learning efficiency. Among them, (B3) the model algorithm in this paper has the greatest improvement on the mastery of knowledge points, and when the learner's progress is 50%, the mastery of current knowledge points is improved as high as 35.18%, and (B2) the Trans-CF algorithm and (B1) the Ontology-CF algorithm are basically the same.

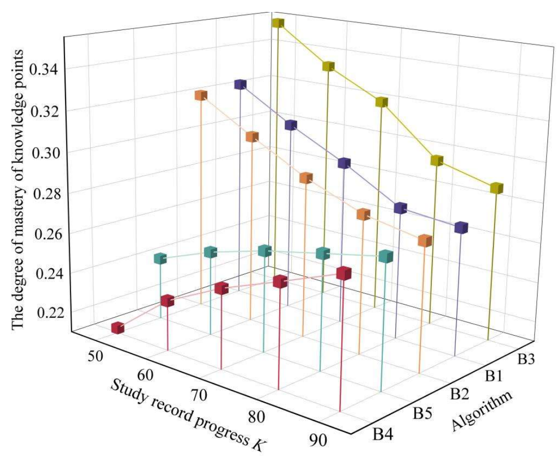


Figure 7: Comparative Experiment on Learning Efficiency

V. Conclusion

In this paper, based on the improved genetic algorithm, a generalized learning path is generated using the knowledge graph. On the basis of the knowledge point sequence of this path, combined with the input parameters of learner characteristics, a personalized learning path matching the characteristics of the learner is output, thus completing the construction of the personalized learning path model for Civic and Political Education. In the assisted learning experiments of this model on learners, when the fusion factor $\alpha = 0.7$, the generated learning path user interest rate and user preference coverage rate are the highest, respectively 77.87% and 51.39%. In comparison with similar modeling algorithms, the degree of mastery of assisted students' knowledge points is most significantly improved, and the assisted mastery is improved by 35.18% when the learning progress is 50%. Through the application of artificial intelligence technology, the research in this paper not only completes the mathematical model of personalized learning path, but also provides effective reference and technical support for the optimization and improvement of the current teaching model of Civic and Political Education.

References

[1] Clegg, S., & Sarker, S. (2024). Artificial intelligence and management education: A conceptualization of human-machine interaction. The International Journal of Management Education, 22(3), 101007.

[2] Ruxiang, L., & Yue, T. (2023). Design and Integration of Interdisciplinary Curriculum Based on Artificial Intelligence. Journal of Intelligence and Knowledge Engineering (ISSN: 2959-0620), 1(3), 75.

[3] Chandra, B., & Rahman, Z. (2024). Artificial intelligence and value co-creation: a review, conceptual framework and directions for future research. Journal of Service Theory and Practice, 34(1), 7-32.

[4] Pratama, M. P., Sampelolo, R., & Lura, H. (2023). Revolutionizing education: harnessing the power of artificial intelligence for personalized learning. Klasikal: Journal of education, language teaching and science, 5(2), 350-357.

[5] Peijie, C. (2018). Smart Education: The educational reform at the age of artificial intelligence. Educational Research, 39(08), 121-128.

[6] Tang, C. (2023). Innovation of Ideological and Political Education Based on Artificial Intelligence Technology with Wireless Network. Eai Endorsed Transactions on Scalable Information Systems, 10(6).

[7] Liu, Z., & Huang, Y. (2024). Innovation in Ideological and Political Education and Personalized Learning Paths in the Era of Artificial Intelligence. International Journal of New Developments in Education, 6(5).

[8] Yang, H., & Shankar, A. (2022). Artificial intelligence-enabled interactive system modeling for teaching and learning based on cognitive web services. International Journal of e-Collaboration (IJeC), 19(2), 1-18.

[9] Xiang, K., & Zhu, Y. (2024). The Influence of Artificial Intelligence Technology on the Optimization of the Teaching Model of Higher Education in the Context of the Pandemic. International Journal of Cognitive Informatics and Natural Intelligence (IJCINI), 18(1), 1-14.

[10] Zheng, G. (2020, April). The optimization and application of blended teaching based on artificial intelligence. In 2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE) (pp. 71-74). IEEE.

[11] Deng, W., Wang, L., & Deng, X. (2024). Strategies for Optimizing Personalized Learning Pathways with Artificial Intelligence Assistance. International Journal of Advanced Computer Science & Applications, 15(6).

[12] Bhutoria, A. (2022). Personalized education and artificial intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. Computers and Education: Artificial Intelligence, 3, 100068.

[13] OLAIDE, A. A. O. A. A., NATHANIEL, S., OYESOLA, O. A. O. O. A., & ABAYOMI, A. K. A. A. K. (2024). ARTIFICIAL INTELLIGENCE WITH AGILE TEACHING STRATEGIES FOR PERSONALIZED LEARNING. Nigerian Online Journal of Educational Sciences and Technology, 6(1), 364-379.