International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 5643-5654

https://doi.org/10.70517/ijhsa463487

Research on Ideological and Political Education Content Generation and Personalized Push Strategy Based on Intelligent Algorithm

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Abstract Traditional teaching methods are difficult to meet the personalized learning needs of students, and the teaching effect is uneven. The application of intelligent algorithms in the field of education provides a new idea to solve this problem, using computer technology to analyze students' learning characteristics and knowledge mastery to realize the intelligent generation and personalized push of the content of ideological and political education. In this study, we constructed a personalized intelligent grouping model of ideological and political education content based on artificial fish swarm algorithm and a personalized test question recommendation model PMF-CD based on probability matrix decomposition, and verified through experiments that the distribution of knowledge points in the test paper generated by the personalized intelligent grouping model is more targeted and aggregated, while the distribution of knowledge points in the traditional grouping method is more dispersed. In the test question recommendation model test, PMF-CD model in DATASET2 dataset 40% test set conditions of the accuracy rate of 98.26%, much higher than the traditional DINA model of 54.39%. Practical experiments show that the experimental class using the model of this study has a significantly higher level of ideology and morality than the control class in the six dimensions of healthy life, ecological civilization, patriotism, scientific spirit, social responsibility and civic literacy, of which the average value of the experimental class in the dimension of patriotism reaches 4.876, while the control class is 4.372, with a significant difference (P<0.000). The results of the study show that the ideological and political education content generation and personalized push strategy based on intelligent algorithms can effectively improve students' ideological and moral level and provide a new path for the modernization of ideological and political education.

Index Terms Intelligent algorithm, ideological and political education, personalized grouping, test question recommendation, artificial fish school algorithm, probability matrix decomposition

I. Introduction

At present, the development of ideological and political education is in a bottleneck, in the context of globalization and networking, students' thinking is impacted, the content of ideological and political education is obsolete, seriously detached from the reality of current affairs, and homogenization is serious, which makes it difficult to meet the students' individualized needs [1], [2]. However, with the rapid development and wide application of artificial intelligence and other digital technologies, the education system is facing unprecedented changes, setting off a new wave of education digital development. The development of education digitalization has profoundly affected the organizational structure, operation mechanism, methods and methods, teaching content and other aspects of ideological and political education, promoting ideological and political education towards digitalization, and promoting the development of ideological and political education in a precise and personalized way [3]-[5].

Intelligent algorithm is a kind of algorithm that uses artificial intelligence technology to solve complex problems, which is based on the principles of mathematics and statistics, can automatically identify the laws, adaptive, learning and optimization, and plays an important role in front and back-end big data analysis [6]. Its ultimate goal is to arrive at the best solution through repeated experimentation, reasoning and solving. It provides a new paradigm for realizing content generation and personalized push for Civic Education. Literature [7] developed a machine learning algorithm-supported pedagogical content formulation that can generate pedagogical content suitable for personalized teaching needs by considering students' needs, educational content diversity, and customized resource limitations. Literature [8] developed an educational resource information recommendation system, which mainly realizes the recommendation of course materials based on students' needs through adaptable genetic algorithms. Literature [9] proposed an APP named GPTutor, which is mainly realized by using generative artificial intelligence, and can generate corresponding educational content and exercises according to students' individualized needs, so as to realize personalized education. And generative AI can be used for the development of higher courses [10].

As an important part of generative AI, Generative Adversarial Network (GAN) is trained by two neural networks that oppose each other, where one generator network is responsible for generating fake data, and the other discriminator network is responsible for distinguishing between generated data and real data. Literature [11] utilizes conditional text GANs that can be customized with text content of varying lengths as per the demand. Literature [12] simplified the problem of sparse interaction data in the generator and discriminator of traditional GAN by conditional GAN to achieve a more accurate personalized recommendation architecture. Literature [13] applied knowledge graph to integrate student behavioral data, determine the available data, and incorporate an improved collaborative recommendation algorithm to accurately recommend students' personalized learning resources, obtaining an accuracy rate of over 90%. Literature [14] integrated Q-matrix theory, long and short-term memory network, and shortest path algorithm to construct a model, predict students' learning difficulty, and recommend materials in line with the learning level, respectively, and constructed a Q-matrix theory-supported learning resource difficulty prediction and Dijestra algorithm, so as to achieve personalized resource recommendation in higher education. Literature [15] designed a personalized recommendation service supported by data portrait technology for the accurate recommendation of knowledge services in Civic and Political Education, and combined association rules, computational scoring matrix, and recursive neural network to optimize the recommendation system accurately.

Ideological and political education is an important way for colleges and universities to cultivate moral and talented people, and it has an irreplaceable role in shaping students' values and improving their ideology and morality. However, with the rapid development of information technology and the continuous growth of students' individualized needs, the traditional ideological and political education model gradually shows many limitations. The traditional ideological and political education content generally adopts a unified and standardized way to organize and push, ignoring the differences between individual students, and it is difficult to provide personalized education content according to the students' knowledge mastery and learning characteristics, which leads to unsatisfactory teaching results. Especially in the case of uneven mastery of knowledge points, the unified teaching content often fails to meet the learning needs of different students, making some students tired of and resistant to the Civics and Political Science course. At the same time, teachers face a heavy workload in the process of preparing lessons and questions, making it difficult to effectively design content for the individual needs of each student. These problems seriously constrain the improvement of the quality of ideological and political education and the advancement of the modernization process. With the wide application of artificial intelligence technology in the field of education, intelligent algorithms provide new technical support and theoretical basis for the personalized generation and pushing of ideological and political education content. Through the accurate analysis of students' learning behavior and knowledge mastery, intelligent algorithms are able to generate ideological and political education content that is suitable for different students and personalized push, thus improving the relevance and effectiveness of ideological and political education. Therefore, it is of great theoretical significance and practical value to study the content generation and personalized delivery strategy of ideological and political education based on intelligent algorithms.

Based on intelligent algorithms, this study constructs a personalized intelligent grouping model of ideological and political education content and a personalized test question recommendation model to realize the intelligent generation and accurate delivery of ideological and political education content. The study will first construct a personalized intelligent grouping model of ideological and political education content based on the artificial fish school algorithm, which analyzes students' knowledge mastery and error-prone question bank, designs multi-dimensional constraints, and generates Civics and Political Science test papers to meet students' personalized needs. Secondly, PMF-CD, a personalized test question recommendation model for ideological and political education based on probability matrix decomposition, is proposed, which realizes accurate assessment of students' mastery of Civics and political knowledge and personalized test question recommendation by combining students' cognitive diagnosis and probability matrix decomposition methods. Finally, the effectiveness of the above model is verified through experiments and practice, and its impact on improving the quality of Civics education and students' ideological and moral level is analyzed. Through this series of research, we explore the application path of artificial intelligence technology in the field of ideological and political education, and provide theoretical guidance and practical reference for promoting the modernization process and improving the quality of Civic and political education.

II. Intelligent Grouping Model for Personalized Ideological and Political Education Content

The application of modern educational technology has become an important part of the ideological and political teaching reform in colleges and universities. This paper will be based on intelligent algorithms, intelligent generation of ideological and political education content and personalized grouping of papers, effectively improving the quality of teachers' work and the modernization of teaching, enriching and optimizing teaching resources.

II. A. Steps for personalized intelligent grouping of papers

In the personalized grouping of ideological and political education content, in order to generate a set of test papers that meets the requirements of the syllabus and satisfies the user's individual learning characteristics, the flowchart of the grouping of the papers, according to the weighting ratio of each parameter, is shown in Figure 1.

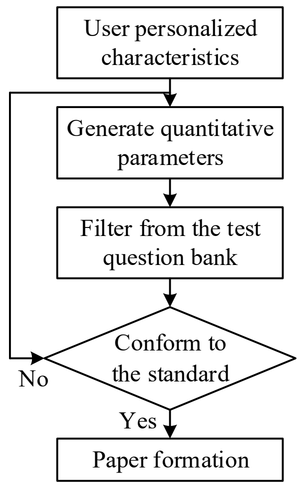


Figure 1: Flowchart

II. B. Constraints on grouping volumes

Ideological and political education personalized test paper is mainly based on the user in a certain behavioral basis to leave the wrong question bank, in the accumulation of a certain number of wrong questions, to start the wrong analysis and wrong prediction, and with the combination of assessment syllabus, in the correction of errors at the same time to ensure that the test paper does not deviate from the focus. Therefore, the constraints of the group paper mainly include: the total score of the test paper, the knowledge point constraints, the topic type constraints, the difficulty of the test paper, and the proportion of easy-to-error questions. In the paper, the five-dimensional space constraints are used to realize the personalized intelligent grouping of the test paper, and then it can be determined that the goal of the test paper is the matrix of the state:

$$P=\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{1}$$

where, m is the total number of all questions in the test paper: n is the number of attributes of each test question. The rows in the objective matrix P represent the attributes of the questions and the columns represent all the attributes of all the questions in the test paper. There are at most $n-1$ constraints on the final test paper, where $a_{i1}(i=1,2,\cdots,m)$ is the ID number of the test question.

II. C. Artificial Fish Swarm Algorithm Design for Personalized Intelligent Grouping of Papers

Artificial fish schooling algorithm is based on the various behavioral activities of fish, through the construction of artificial fish to mimic the foraging, schooling and tail chasing behavior of the fish, so as to achieve the search for the optimal, and finally make the global optimal value in the group to be revealed, in the multi-constraint multi-strategy solving problems, the fish schooling algorithm can achieve satisfactory results [16].

Artificial fish swarm algorithm for lower-dimensional problems, can be better jump out of a small range of extreme values, quickly search for the optimal value of the entire range, and the algorithm has many advantages, such as the initial value and parameter selection requirements are not high, the algorithm is more stable, and the algorithm updating mechanism is simple, easy to operate is also convenient to improve in order to be applied to practical problems.

The basic idea of the algorithm is: the feasible domain of the objective function is a piece of water, and each individual fish in the water is a feasible solution to the objective function, simulate the behavior of the fish foraging, you can realize the global search for the optimal, combined with the intelligent grouping of each artificial fish represents a combination of test programs, through the search for the optimal process, and finally get the optimal combination of test questions is also the most in line with the constraints of the test paper.

1) Pre-processing

In the use of artificial fish grouping algorithm before the paper, the need for test bank data preprocessing work, first of all, the test questions in accordance with the question type for classification, the same type of questions into a category, which will be divided into a number of different categories of the test bank, the number of different types of questions between the processing.

2) Coding method

Each fish is encoded using a binary encoding method, represented using the m -dimensional vector $X=(X_1,X_2,\cdots,X_m)$. The required number of dimensions of the directed quantity determined by the number of test papers, the components of the vector $X_i(i=1,2,\cdots,n)$ denote the test attributes and n is the number of test attributes.

3) Objective function

The objective function is used in the artificial fish schooling algorithm to calculate the food concentration, the total score, the proportion of knowledge points, the proportion of questions, the difficulty of the test paper and the proportion of easy questions in the test paper that meets the conditions of these constraints in the ideal state should be exactly the same as the set value or within a certain margin of error can be accepted. The result of the weighting calculation between the parameters of the generated question paper and the set values determines the size of the objective function Y. Only when the Y value is minimized, the generated paper is the one that meets all the requirements, i.e., the state of high food concentration. The objective function is calculated according to the following formula:

$$\begin{aligned} Y =& \left|\sum_{j=1}^{k}\left(\sum_{i=1}^{m}a_{i3}k(j)-S_k^j\right)\right|\cdot w_1 \\ &+\left|\sum_{j=1}^{t}\left(\sum_{i=1}^{m}a_{i4}t(j)-S_i^j\right)\right|\cdot w_2 \\ &+\left|\left(\sum_{i=1}^{m}a_{i2}a_{i5}\right)/S_p-DIF_p\right|\cdot w_3 \\ &+\left|\sum_{j=1}^{y}\left(\sum_{i=1}^{m}a_{i6}y(j)-S_y\right)\right|\cdot w_4 \end{aligned} \tag{2}$$

There is no constraint on the total marks of the paper due to the fact that the total marks are set to a constant value during the initialization process, where k represents the total number of knowledge points of the course and t represents the total number of question attributes in the formula.

4) Steps of the algorithm

Step 1: Initialization of artificial fish parameters. Assuming that the population number of artificial fish is m and the dimension of each artificial fish is n, the location information of each artificial fish is initialized. All the test questions in the question bank are numbered, for example, categorized according to the question type, and then the same categories are regularized and put into an array for management, and the continuity of the array can be numbered operation on the questions.

Step 2: Determine the number of each question type in the test paper. Each question type has a certain score constraints, through the score constraints can naturally calculate the number of questions required for each question type, through this constraint can make the initialization process to ensure that the sum of the scores of each question type to meet the constraints of the demand.

Step 3: Setting parameters. To initialize the state of the fish school, firstly, the operation of extracting test questions from the question bank is carried out, and the number of questions meets the requirements of the constraints, and at the same time, the maximum allowable distance between the fish schools is set to V, the maximum number of moving steps of the artificial fish is set to S, and the maximum crowding factor is set to δ and other parameters.

And the food concentration in the fish group is represented by the objective approximate function Y, the smaller the value of Y, the higher the state that the artificial fish is in, and the more the generated paper meets all the constraints.

Step 4: Initialize the bulletin board. Through the test question number corresponding to the current state of the fish, calculate whether the relevant attributes comply with the objective function constraints, record the state value with the smallest objective function value in the current state and the corresponding objective function value on the bulletin board and replace the old value, and wait for comparison with the value of the next fish.

Step 5: Update the bulletin board. The artificial fish in the school are compared and the best state with the smallest objective function value is selected, e.g., tail chasing and schooling behavior are simulated to update the iteration so that the value on the bulletin board is the optimal value, and if it is less than the value, the value is replaced, and if it is less than the value, the value is left unchanged.

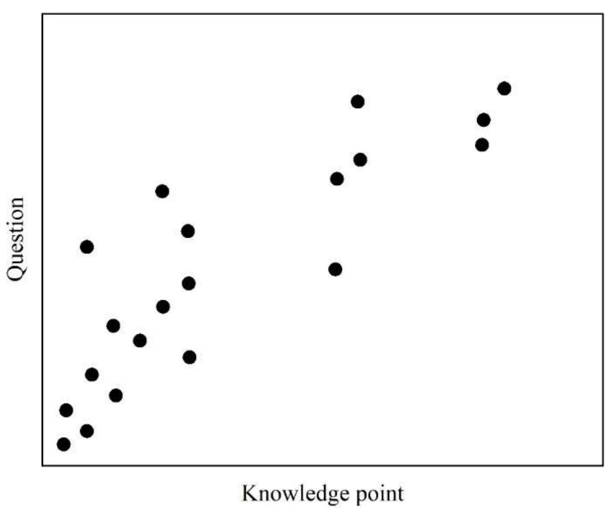
Step 6: Termination. Repeat steps 4 and 5 until the value of the objective function on the bulletin board is minimum, or the number of cycles of comparison is greater than the constraints, and then output the optimal test paper.

Analyze the user's weaknesses, obtain his wrong question bank, perform classification and generalization to calculate the weight of each of the wrong constraints, bring them into the above algorithm, and perform an iterative loop to guide to find the test paper that best meets each of the conditions.

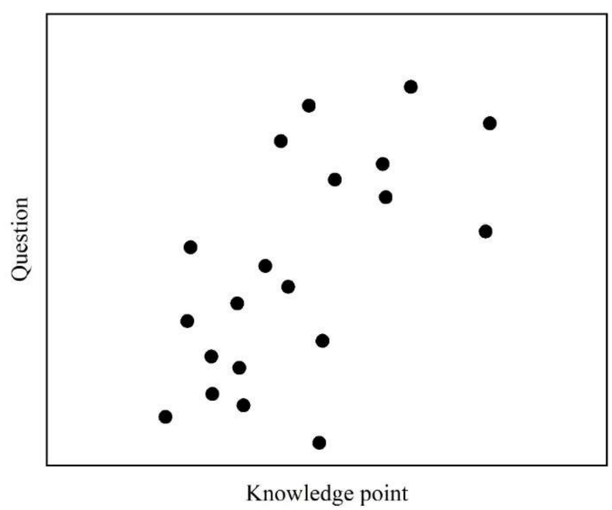
III. Simulation Experiment on Personalized Grouping of Ideological and Political Education Content

In order to verify the performance of the personalized intelligent grouping model of ideological and political education content proposed in this paper, the experiment selected the 120 students who took the course of Ideological Ethics and the Rule of Law on the general practice evaluation platform of a school and studied the course as the research object, of which 569 Civic and Political Question Bank data sets.

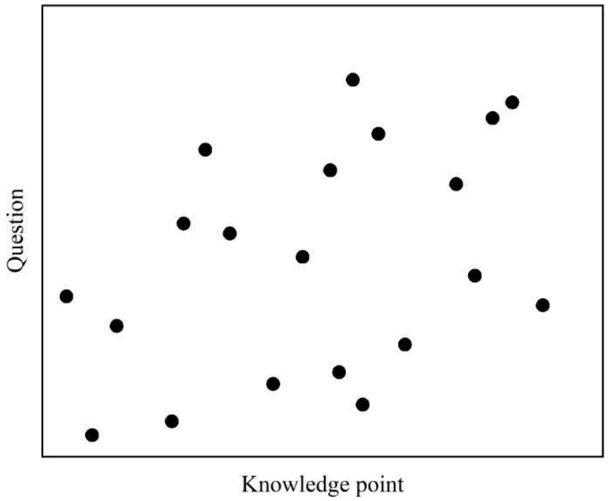
The Civics and Politics question bank data are applied to the personalized intelligent grouping model proposed in this paper and the traditional grouping model to compare and analyze the generated knowledge distribution, as shown in Figure 2. Figures (a) and (b) show the distribution of the exercise knowledge points generated according to the personalized intelligent grouping model of this paper, and Figures (c) and (d) show the distribution of the knowledge points based on the traditional grouping method. From the figure, we can see that the test paper generated by this paper's model has a greater difference in the distribution of knowledge points, and the distribution of knowledge points is more aggregated, which is because it is selected according to the degree of mastery of students' knowledge points. The traditional method of organizing papers is basically the same in the distribution of knowledge points, and more scattered without reinforcement. In contrast, the personalized intelligent grouping model of ideological and political education proposed in this paper can provide different personalized exercises for students' individual differences.



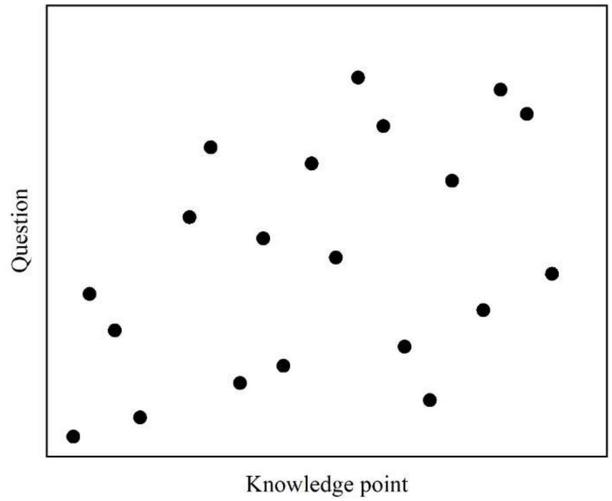
(a)Test results of the model in this paper 1



(b)Test results of the model in this paper 2



(c)Test results of traditional methods 1



(d)Test results of traditional methods 2

Figure 2: Knowledge distributing

IV. Personalized Test Question Recommendation Model for Ideological and Political Education

In the above paper, this paper proposes a personalized intelligent grouping model for ideological and political education content based on intelligent algorithms, which provides different personalized test question training based on students' personalized differences. In this chapter, a new personalized test question recommendation model PMF-CD for ideological and political education is proposed on this basis.

IV. A. *Overall framework of the PMF-CD methodology*

This section describes the technical scheme of PMF-CD proposed in this paper.The overall process of PMF-CD is divided into 3 main steps:

1) Input: students' doing R matrix and test question knowledge point association Q matrix (labeled by experts in the field).

2)Student cognitive diagnosis (step 1): use DINA model to model students' knowledge point mastery, obtain students' knowledge point mastery, and model students' mastery level on the Civics test questions based on their mastery on the knowledge points [17].

3) Student Score Prediction (Step 2): Combine the PMF model and introduce the students' mastery on the test questions and the examination of the knowledge points of the Civics test questions to be recommended as the a priori of the student's potential factor and the test question's potential factor, and predict the student's score on the test questions accordingly [18].

4) Output (Step 3): According to the actual demand, set the difficulty range of the Civics questions $[\beta_1, \beta_2]$ for the test questions to be recommended relative to the Civics questions for the students to be recommended, and screen the test questions whose probability of correctly answering by the students is within the recommended difficulty range, so as to make a personalized test question recommendation to each student.

IV. B. *Specific practices of the PMF-CD methodology*

The PMF-CD method proposed in this paper will combine the DINA model and PMF for student performance prediction as a basis for ideological and political test recommendations.

IV. B. 1) Student Cognitive Diagnosis

When using the DINA model to model the degree of mastery of students' knowledge points in Civics and Politics, in response to the shortcomings of the DINA model that can only give the discrete degree of mastery of students' knowledge points (only mastery and non-mastery of two kinds), this paper obtains this probabilistic degree of mastery of students' knowledge points in Civics and Politics by considering all possible α posterior probabilities, so that it can probabilistically model students' degree of mastery of knowledge points and modeling the mastery degree of students' knowledge points of Civics as continuous values between 0 and 1. Redefine the estimated skill vector $\tilde{\alpha}_u$ and calculate the degree of mastery of skill S_k by student P_u according to the following equation (3):

$$\hat{\alpha}_{ak} = P(\alpha_{ak} = 1 \mid R_a) = \frac{\sum_{a_{ak}=1} P(\alpha_x \mid R_a)}{\sum_{x=1}^{2^K} P(\alpha_x \mid R_a)} = \frac{\sum_{a_{xk}=1} L(R_a \mid \alpha_x, \hat{s}_V, \hat{g}_V) P(\alpha_x)}{\sum_{x=1}^{K} P(\alpha_x \mid R_a)} = \frac{\sum_{a_{xk}=1} \prod_{v=1}^{V} L(R_w, \mid \alpha_x, \hat{s}_V, \hat{g}_V) P(\alpha_x)}{\sum_{z=1}^{2^K} P(\alpha_x \mid R_a)} \tag{3}$$

With the known discrete degree of students' mastery of Civics knowledge points, this paper calculates the real level of students' performance on the test questions, i.e., the true level of students after excluding mistakes and guesses from the known students' answers to the test questions, by taking the already observed students' answers and the corresponding test questions' skill requirements as a priori.

For the true level A_{uv} of how well student P_u answered the questions on test J_v, this paper first calculates the student's average skill mastery S_{avguv} on the skills required for the test questions using geometric means:

$$S_{avguv} = \sqrt[\frac{1}{\sum_{k=1}^{K} q_{uvk}}]{\prod_{k=1}^{K} In_{uvk}} \tag{4}$$

where In_{uvk} is:

$$In_{uvk} = \begin{cases} 1, & q_{vk} = 0 \\ \alpha_{uk} \cdot q_{vk}, & q_{vk} = 1 \end{cases} \tag{5}$$

The true level in the student's answering situation is calculated by equation (6) with the actual student's answering and the guessing rate g_v and error rate s_v of the test questions obtained from the DINA model as the a priori parameters, provided that the student's average mastery of the skills required in the test questions is known:

$$A_{uv} = \begin{cases} \dfrac{(1-s_v)S_{avguv}}{(1-s_v)S_{avguv} + g_v(1-S_{avguv})}, & R_{av} = 1 \\ \dfrac{s_v S_{avguv}}{s_v S_{avguv} + (1-g_v)(1-S_{avguv})}, & R_{av} = 0 \end{cases} \tag{6}$$

At this point, step 1 of the student cognitive diagnosis of the recommended methodology for the PMF-CD test questions was completed.

IV. B. 2) Prediction of student scores

After obtaining the student cognitive diagnostic information, it is used in the probability matrix factorization (step 2). Specifically, the feature b_{uv} can be extracted from the true level matrix A of students' answers as a priori information for PMF:

$$\begin{aligned} b_{uv} &= b_u + b_v \\ b_u &= \frac{1}{V} \times \sum_{i=1}^{V} A_{ui} \\ b_v &= \frac{1}{U} \times \sum_{i=1}^{U} A_{iv} \end{aligned} \tag{7}$$

where b_u denotes the a priori degree of students' P_u learning scores, which reflects the differences in the degree of mastery of knowledge points among students, and is the average of the u th row of the matrix A. b_v denotes the a priori degree of scores of the test questions v, which reflects the differences in the degree of difficulty of the questions among them, and is the average of the v th column of the matrix A. By considering the the degree of students' knowledge point mastery, b_u, b_v can realistically reflect the students' individual learning status, which is the basis for the subsequent work.

After adding the a priori b_u and b_v of students and test questions, the cognitive diagnosis-based modeling method of answering situation in the personalized test recommendation method PMF-CD proposed in this paper is obtained, under which the potential answering situation of students η_{uv} is obtained by the following equation (8):

$$\eta_{uv} = \mu + \rho b_{uv} + (1-\rho) M_u^T N_v \tag{8}$$

where μ is the overall average score. In Eq. (8), the proportion of students' individualized learning states and common learning states among students in η_{uv} prediction is regulated by the parameter ρ, $\rho \in [0,1]$. A larger ρ indicates that the predicted score is more influenced by the individuality of the student's learning state; a smaller ρ indicates that the predicted score is more influenced by the commonality of the student's learning state. In particular, when $\rho = 0$, the individualized learning states of students are not introduced, and the method degenerates into PMF.By adding the individualized learning states of students b_{uv} to the PMF decomposition, the low-dimensional latent factors M, N decomposed by PMF can be made to incorporate the individuality characteristics of students while including the learning states that are common among them, and thus the score prediction can improve the score prediction accuracy and interpretability of the results.

The student's answer prediction consists of four components: overall mean, test prior, student prior, and student-test interaction, each of which explains a certain property of the observation, then the optimization objective of PMF-CD can be changed to minimize the functional formula:

$$E = \sum_{u=1}^{U}\sum_{v=1}^{V} I_{uv}(R_{uv} - \eta_{uv})^2 + \lambda_M \| M \|_{Fro}^2 + \lambda_N \| N \|_{Fro}^2 \tag{9}$$

where λ_M, λ_N is the regularization factor of the model.

IV. B. 3) Test question recommendation based on student score prediction

In the PMF-CD test question recommendation method, the difficulty of the recommended Civics test questions can be set according to the user's needs. The difficulty of the test questions refers to the difficulty of the test questions relative to the students, and the probability that a student P_u correctly answers the test question J_v is taken as the difficulty J_v of the test question D_{uv} for the student P_u, that is:

$$D_{uv} = P(r_{uv} = 1 \mid P_u, J_v) \tag{10}$$

When performing Civics test question recommendation, the recommended Civics test question difficulty range $\beta_1, \beta_2 (\beta_1 < \beta_2)$ is set as the recommended test question difficulty boundary, and the PMF-CD can recommend to the student P_u a test question set J_{rec_u} whose probability of correctly answering is between β_1 and β_2 from the set of test questions to be recommended J_{rec} based on the student's potential response η_{uv}:

$$J_{rec_u} = \{J_v \mid J_v \in J_{rec}, D_{uv} \in [\beta_1, \beta_2]\} \tag{11}$$

where β_1 is the lower bound of the probability of students answering correctly, and β_2 is the upper bound of the probability of students answering correctly, therefore, after setting the corresponding difficulty range of the recommended Civics test questions, PMF-CD can recommend the test questions within the corresponding difficulty range to each student.

Since PMF-CD personalized Civics test recommendation method effectively combines the individuality of students' own Civics learning situation and the commonality of learning situations among students when recommending test questions, the recommended Civics test questions can reflect the current Civics learning status of the students, and it can recommend personalized test questions with appropriate difficulty levels for the students.

V. Ideological and Political Education Individualized Test Question Recommendation Simulation Experiment

In this chapter, simulation experiments on personalized test question recommendation for ideological and political education will be carried out to test the performance of the personalized test question recommendation model for ideological and political education constructed in this paper.

V. A. *Experimental data set*

For the experimental data, three data sets were used for comparison, all of which were from the real experiment. The information about the three datasets is shown in Table 1.The DATASET1 dataset corresponds to the answers of 536 secondary school students to 15 subtraction questions, which examined a total of 5 knowledge points.The DATASET2 dataset corresponds to the answers of 757 students to 23 math questions, which examined a total of 15 knowledge points. The DATASET3 dataset examined only 4 knowledge points and corresponded to 1710 middle school students answering 17 questions.

Table 1: Detailed data of experimental dataset

Dataset	Students	Test questions	Knowledge points
DATASET1	536	15	5
DATASET2	757	23	15
DATASET3	1710	17	4

V. B. *Analysis of experimental results*

According to different test sets, the proposed personalized test question recommendation model PMF-CD for ideological and political education in this paper is compared experimentally with the traditional DINA model, and the experimental results are specifically shown in Table 2. It can be observed that the PMF-CD model of this paper is better than the traditional DINA model in terms of accuracy and recall, and it is more reliable and persuasive to recommend questions to students by combining the knowledge mastery of similar users of the target users. When the ratio of test questions in the test set is small, the traditional DINA model is unable to accurately infer the students' knowledge status, and the fluctuation of the recommendation results is large, which is mainly due to the reduction of the training data, which leads to a large error in the traditional DINA model for the students' knowledge mastery status. As the number of students increases, the performance of the PMF-CD model in this paper becomes more and more superior, indicating that for a large number of students' scoring data in real life, the model in this paper can efficiently and accurately analyze the state of students' mastery of knowledge points, and make personalized test recommendations for different students.

Table 2: Experimental result

Index	Model	DATASET1 Test Set Ratio (%)			DATASET2 test set ratio (%)			DATASET3 test set ratio (%)		
		30	40	50	30	40	50	30	40	50
Precision rate	DINA	32.32	36.6	35.83	49.74	54.39	59.64	53.78	60.63	63.51
	PMF-CD	86.71	95.03	81.85	84.32	98.26	95.52	97.82	93.75	83.24
Recall rate	DINA	12.67	14.38	13.94	37.38	29.21	24.53	36.73	31.34	26.88
	PMF-CD	16.64	25.77	32.95	11.19	17.06	21.08	17.3	22.34	25.84
F1 value	DINA	18.08	20.53	20.02	42.69	38.11	34.81	43.61	41.31	37.69
	PMF-CD	22.23	40.34	46.95	11.53	19.75	34.33	29.42	36.17	39.45

VI. Personalized Grouping and Test Question Recommendation Civic Education Practice

This chapter will apply the personalized intelligent grouping model of ideological and political education content and the personalized test question recommendation model proposed in this paper to the real ideological and political teaching classroom, and explore its impact on students' ideology and moral character.

VI. A. *Selection of experimental subjects*

This paper takes the first year students of Chinese language and literature major in a university as the research object, and carries out a 3-month practice of personalized grouping of papers and test question recommendation for ideological and political education based on the ideological and political course. In the process of practice, two classes in which students' ideology and morality are basically at the same level are selected as the experimental class and the control class, and the experimental class will use the personalized intelligent grouping model of ideological and political education and the personalized test question recommendation model proposed in this paper to the teaching of Civic and Political Education, while the control class maintains the existing teaching method of Civic and Political Education. Before and after the experiment, the “Questionnaire on the Status of Students' Ideological and Moral Status” was used to test the students' ideological and moral status.

VI. B. Questionnaire design

The "Survey Questionnaire on the Current Situation of Students' Ideological and Moral Status" is divided into 6 dimensions and consists of a total of 25 questions, corresponding to: Healthy Living (Questions 1-5), Ecological Civilization (Questions 6-10), Patriotism (Questions 11-13), Scientific Spirit (Questions 14-15), Social Responsibility (Questions 16-20), and Civic Literacy (Questions 21-25). Each question has 5 options, specifically: "completely matches me," "mostly matches me," "uncertain," "mostly does not match me," and "completely does not match me," with scores decreasing from 5 points to 1 point.

The scale was tested for reliability and validity using SPSS 25.0 statistical software, and the reliability a value of each dimension was greater than 0.7, and the KMO value was 0.945, which was higher than 0.7, and there was a strong correlation between the variables. And the significance of Bartlett's spherical test is 0.000, which is less than the significance level of 0.05, indicating that the variables are suitable for factor analysis. Therefore, the validity of the scale questionnaire is good and suitable for further analysis.

VI. C. Analysis of experimental results

1) Analysis of experimental class ideological condition before and after practice

An independent sample T-test was conducted for the indicators in the questionnaire of the experimental class students before and after the practice, and the specific results are shown in Table 3. As can be seen from the table, the P-values of the six dimensions of healthy life, ecological civilization, patriotism, scientific spirit, social responsibility, civic literacy, etc. are all 0.000, which are all less than 0.05, which indicates that there is a significant difference between the experimental class before and after practice in the level of ideology and morality, and the mean values are higher than the pre-practice ones, which indicates that the application of the personalized intelligent grouping model of the content of ideological and political education and the personalized test question Recommendation model in the teaching of ideological and political courses has a significant impact on the improvement of students' ideological and moral level.

Table 3: Independent Sample T-Test before and after Practice in Experimental Class

Dimensions	Time phasing	Mean value	Standard deviation	T	P
Healthy life	Before practice	3.595	0.672	-6.896	0.000
	After practice	4.32	0.268		
Ecological civilization	Before practice	3.778	0.639	-6.653	0.000
	After practice	4.47	0.308		
Patriotism	Before practice	4.395	0.516	-6.025	0.000
	After practice	4.89	0.207		
Scientific spirit	Before practice	3.456	1.041	-5.204	0.000
	After practice	4.326	0.488		
Social responsibility	Before practice	3.676	0.757	-7.342	0.000
	After practice	4.578	0.335		
Civic literacy	Before practice	4.068	0.621	-8.208	0.000
	After practice	4.825	0.203		

2) Analysis of the state of mind of the experimental class and the control class after practice

The independent samples T-test was conducted on the dimensions of the ideological and moral status of the 2 classes of the experimental class and the control class after practice, and the test results were specifically shown in Table 4. As can be seen from the table, the P value of the two classes in the 6 dimensions of ideological and moral status of healthy life, ecological civilization, patriotism, scientific spirit, social responsibility, civic literacy and so on is 0.000, which is less than 0.05, which explains that after the practice of the two classes, the difference between the students in the 6 dimensions of ideology and morality is significant, and the average level of students' ideology and morality of the experimental class is higher than that of the control class. On the other hand, it shows that the application of the personalized intelligent grouping model of ideological and political education content and the personalized test question recommendation model proposed in this paper in the teaching of the Civics and Political Science course has a significant effect on the improvement of students' ideological and moral level.

Table 4: Independent sample T-test in two classes after practice

Dimensions	Class	Mean value	Standard deviation	T	P
Healthy life	Experimental class	4.316	0.271	6.122	0.000
	Control class	3.562	0.813		
Ecological civilization	Experimental class	4.457	0.309	5.426	0.000
	Control class	3.809	0.768		
Patriotism	Experimental class	4.876	0.198	6.356	0.000
	Control class	4.372	0.499		
Scientific spirit	Experimental class	4.331	0.487	4.755	0.000
	Control class	3.525	1.029		
Social responsibility	Experimental class	4.564	0.338	6.246	0.000
	Control class	3.649	0.93		
Civic literacy	Experimental class	4.832	0.215	4.776	0.000
	Control class	4.122	0.993		

VII. Conclusion

This study constructed a personalized intelligent grouping model of ideological and political education content and a test question recommendation model based on intelligent algorithms, which effectively improved the level of personalization of Civic and Political Education. The research results show that the personalized intelligent grouping model based on the artificial fish school algorithm can generate targeted test papers according to students' knowledge mastery, and the distribution of knowledge points in the generated test papers is more aggregated and enhanced, which effectively improves the targeting of Civic and Political Education. The PMF-CD model based on probabilistic matrix decomposition performs well in test question recommendation, with an accuracy rate of 83.24% and an F1 value of 39.45% under the conditions of DATASET3 dataset, which is significantly better than the 63.51% and 37.69% of the traditional DINA model. In the practical experiments, the average score of the experimental class applying the model of this study reaches 4.564 on the social responsibility dimension, which is 25.1% higher than the 3.649 of the control class; the average score of the experimental class on the civic literacy dimension is 4.832, which is 17.2% higher than the 4.122 of the control class. This shows that the model constructed in this study can effectively promote the improvement of students' ideological and moral level. The research results not only break through the limitations of the traditional way of generating and pushing the content of ideological education, but also provide new ideas and methods for the modernization and transformation of ideological education. Future research can further explore the in-depth application of intelligent algorithms in Civic and Political Education, optimize the model performance, expand the scope of application, and provide theoretical and technical support for the construction of an intelligent, personalized, and efficient Civic and Political Education system.

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