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Article

Research on Personalized Learning Path Construction of College Short Video Platform Based on Dynamic Content Optimization Algorithm

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Abstract: The study designed a dynamic genetic algorithm based on dynamic content with multi-adaptation by setting stopping criterion, cost function optimization and other strategies, and constructed personalized learning paths in short video platforms in colleges and universities by this algorithm. In order to more accurately realize the personalized learning path recommendation, the learner model and the learning resource model are constructed, and at the same time, according to the mapping relationship between the two, multiple objective functions such as the cognitive level of the learner and the learning style are determined. Combined with the improved optimization algorithm, the personalized learning path construction problem is solved to complete the personalized learning path construction under the short video platform. The algorithm in this paper iterates 140 times, and the objective function converges to about 12, which is faster and better than the convergence speed of the comparison algorithm. Through personalized learning path recommendation, the average grade of students in the experimental group is improved by 7.4 points compared with the control group, which is a significant difference. Under the personalized learning path recommendation, the average time for students to learn the knowledge points in the college short video platform drops dramatically, and the average learning time is only 65.36 min. the multidimensional scores of the students for the personalized learning path are 4.12-4.72, in which the path needs to be further improved for the improvement of learning efficiency.

Keywords: dynamic content optimization algorithm; genetic algorithm; personalized learning path; short video platform

1. Introduction

With the continued development of the internet, users' information needs have become increasingly fragmented and mobile. Since 2014, internet download speeds have continued to improve. Against this backdrop, new product forms represented by short videos have developed rapidly, becoming an important component of the social information content ecosystem [1-2]. Users generate content while using the internet, thereby serving as both creators and consumers of platform content. Short videos differ from traditional entertainment and leisure activities, having evolved into a platform for mass creation, participation, and sharing. With their ease of dissemination, strong interactivity, and broad coverage of knowledge domains, they are more readily accepted by the public [3-5]. As of December 2024, the number of short video users reached nearly 1.04 billion, accounting for 93% of internet users, with a usage rate of 93.8%. Among them, the usage rate of short video users aged 20-29 was approximately 86%, ranking third among all age groups [6]. Douyin launched initiatives such as the “Qingjiao Plan” and “DOU Knowledge Plan” to encourage professional creators to produce knowledge-based content, attracting experts from various academic fields, teachers, education bloggers, science popularization bloggers, and prominent students to participate. Additionally, Douyin established a micro-learning section, where videos popularizing knowledge across various disciplines have gained significant user favor and are receiving particular attention in the education sector [7-10]. Short videos are not only one of the platforms for students to obtain information but also an important channel for them to seek answers to questions and acquire knowledge. The light knowledge content presented in video format is highly operational and instructive, aligning well with students' intuitive and visual cognitive characteristics [11-13]. Therefore, in the mobile internet environment, combining "short videos" with online education has formed a new teaching model of "short videos + education," which has also become an effective pathway for personalized learning.

Using short videos for learning is an inevitable trend in the development of education and short video platforms. Literature [14] reviews how short videos enhance students' attention, curiosity, engagement, understanding, learning motivation, critical thinking, creativity, and peer collaboration, thereby improving learning outcomes. Literature [15] found that under the support of various algorithms, Douyin promotes students' enthusiasm and interaction through personalized content and multimedia functions, enabling effective micro-learning. Literature [16] constructed a personalized combination recommendation model for information enhancement and knowledge point overlap information, used for recommending short video online learning resources, providing support for students' personalized learning on short video platforms. However, there is currently no research on constructing personalized learning paths for students on short video platforms.

Literature [17] used structural equation modeling to analyze student satisfaction with learning on short video platforms, finding that student satisfaction significantly responds to perceived usefulness and enjoyment of the platform, product novelty, and privacy protection. However, literature [18] explored that watching short videos driven by specific problems helps improve user engagement and focus, but learning benefits decline in entertaining short videos. Therefore, constructing personalized learning paths for students on university short video platforms requires consideration of the platform's practical value, moderate fun, and novelty to provide a better environment for students' digital learning.

The article optimizes the core parameters and steps in the traditional genetic algorithm, and in this way develops a multi-adaptive dynamic genetic algorithm based on dynamic content optimization. In addition, the feature information of learners and learning resources in the learning path construction problem is analyzed, and a personalized learning path model based on learner information and learning resource information is constructed. Meanwhile, multi-objective functions such as learner's cognitive level are proposed, and the weighted summation method is used to integrate the multi-objective functions into a single objective function. Combined with the personalized learning path construction framework, the improved genetic algorithm is used to optimize the solution, and simulation experiments on algorithm optimization performance are carried out based on simulation software. The generated personalized learning path is applied to a university for instance analysis, and the effectiveness of the path is judged by evaluating the learner's performance, learning time and other indicators.

2. Methodology

2.1. Dynamic Content Optimization Algorithm Design

In this study, the traditional genetic algorithm [19] is optimized and improved, and a multi-adaptation dynamic genetic algorithm based on dynamic content optimization is designed, and the algorithm is used to carry out research on the construction of personalized learning paths for efficient short video platforms. The specific improvement process is as follows.

2.1.1. Chromosome Coding and Decoding

In this paper, we use resource-task indirect coding: the length of the chromosome is the total number of learning path nodes, each locus represents a task, the locus number is the task number, and the bit value of the locus represents the number of the corresponding learning resource assigned to the task.

2.1.2. Initial Population Generation

Let the population size be SCALE, the total number of tasks be M, and the number of resources be N. The initialization process of the population can be described as follows: randomly constructing SCALE chromosomes, each of which is CloudletNum in length, and the bit value of each gene is randomly taken in the range of [1,N]. In order to effectively respond to the dynamic change of content optimization, the following improvements are also required:

In the short video platform environment, computational nodes may change at any time and dynamically join or leave. If a computing node leaves, the state of the resource is set to unavailable at the beginning of the next round of optimization, and the number occupied by the resource is removed from the resource number sequence. Each gene position takes a value from N to N-1, and then a new population is generated. If the computational node is to be joined, then at the beginning of the next round of optimization, change the status of the resource from unavailable to available, add a new number to the current resource numbering sequence, and the range of values for each gene position in the chromosome is changed from N to N+1, and generate a new population according to this new sequence.

2.1.3. Choice Operator Optimization

Selection operator is a way for genetic algorithms to evaluate individual chromosomes according to the fitness function, and it also ensures that the good genes in the parent chromosomes can be inherited into the offspring chromosomes. The specific method is to calculate the fitness of each individual in the current population separately, and adopt a certain method to select the parent individuals with higher fitness to inherit their genes to the offspring. In this paper, the roulette algorithm [20] is selected to realize the selection operator.

2.1.4. Discontinuation Guidelines

A threshold N can be set to terminate the operation if the fitness of the optimal chromosome in the population remains unchanged for N consecutive generations and is optimal for all generations. The calculation formula is as follows:

$$|F_{\max} - \bar{F}| < \varepsilon \text{ or } \sum |F_i - \bar{F}| < \varepsilon \tag{1}$$

2.1.5. Re-Selection Strategies

The study adopts a reselection strategy, which is done by sorting the population obtained from the selection operation and the population obtained from cross mutation by fitness, taking the optimal half of them, and synthesizing a new population. This dominant population will be closer to the optimal solution than the original two populations, contains more excellent individuals, and can undergo fewer iterations to search for the global optimal solution.

2.1.6. Optimizing the Cost Function

In this paper, the concept of "optimization cost" is proposed to evaluate the advantages and disadvantages of the current weights of the objective function, which is defined as follows:

Optimization cost (OC): for the same task scheduling scenario, set the optimization weights $\{(\alpha_1, \beta), (\alpha_2, \beta_2), ..., (\alpha_n, \beta_n)\}$, where $\alpha_k (1 \le k \le n)$ represents the weight of the time optimization objective and $\beta_k (1 \le k \le n)$ represents the weight of the energy consumption optimization objective. When the weights are set to (α_k, β_k), the consumed time is denoted as $Time_k$, and the consumed energy for path generation is denoted as $Power_k$, then the optimization cost denotes the cost of the optimization when the optimization weights change from $(\alpha_{k-1}, \beta_{k-1})$ changes to (α_k, β_k). The time cost to achieve the reduction in energy consumption is the ratio between the time cost and the optimized energy consumption value, calculated as:

$$OC = \frac{\Delta Time}{\Delta Power} = \left| \frac{Time_k - Time_{k-1}}{Power_k - Power_{k-1}} \right| \tag{2}$$

2.1.7. General Flow of the Algorithm

The flow structure of the proposed multi-adaptation dynamic genetic optimization algorithm in this paper is shown in Fig. 1.

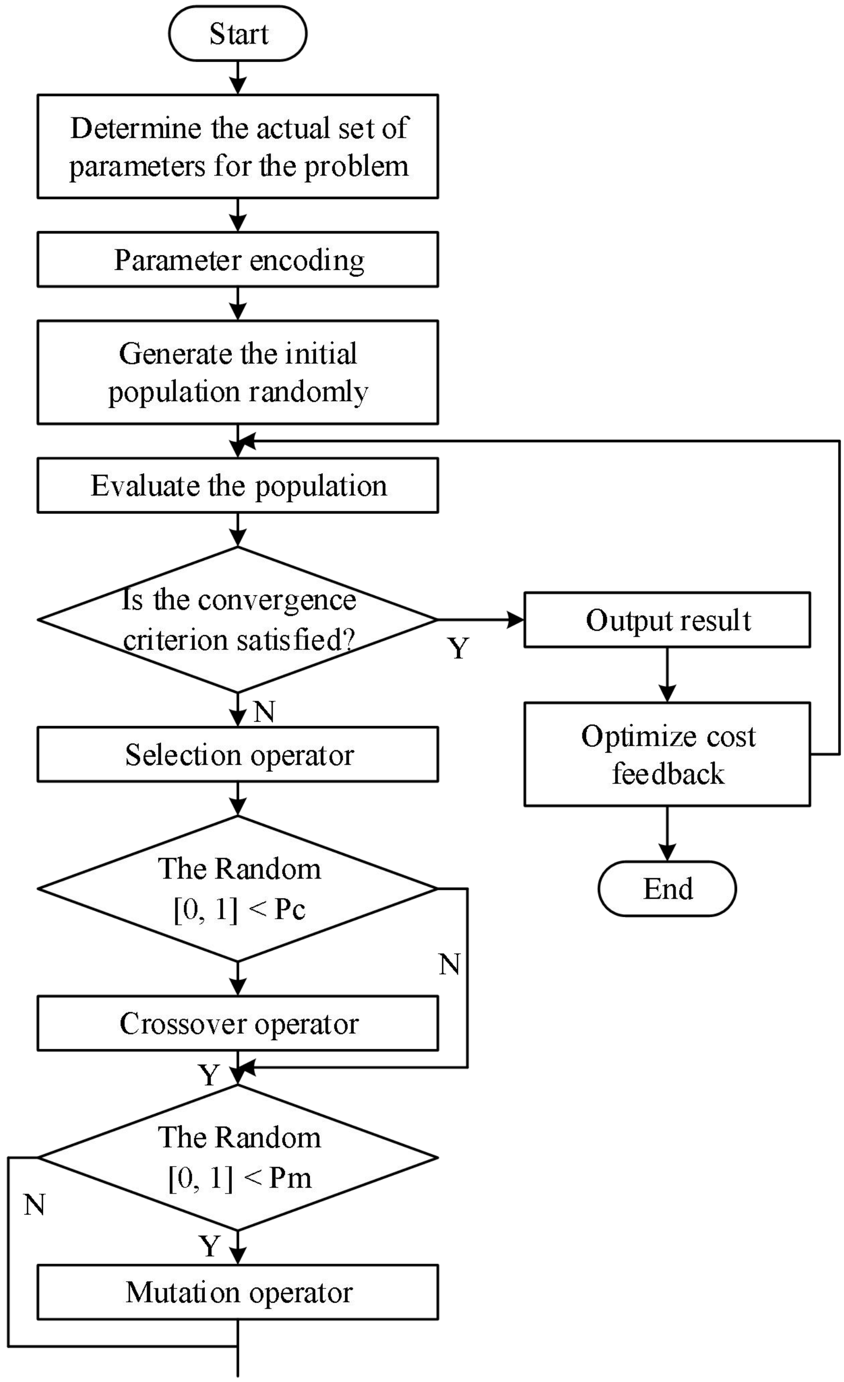

Figure 1. Multi-fitness dynamic genetic optimization algorithm process.

2.2. Personalized Learning Path Generation Model

The structural relationships defined in this paper contain precedence, subsequence, and juxtaposition relationships. If target knowledge point B can be mastered only after knowledge point A is learned, it means that A is the prior order knowledge point of B, and B is the posterior order knowledge point of A. However, if target knowledge points E and F are learning tasks at the same stage of the learner's learning and there is no relationship between the knowledge points, E and F are indicated to be in a juxtaposition relationship. Figure 2 illustrates the structure of knowledge point relationships.

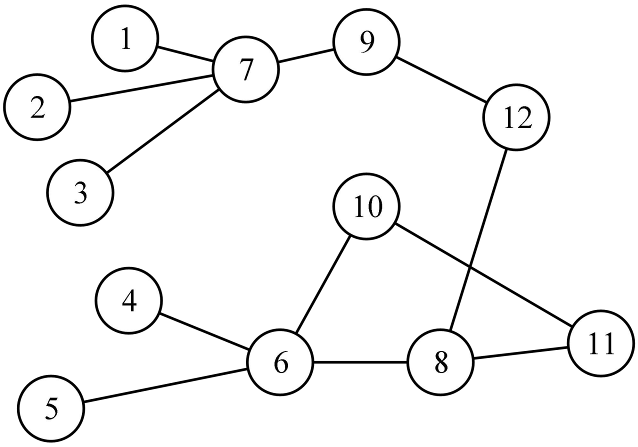

Figure 2. Knowledge Point Relationship Structure Diagram.

2.2.1. Learner Model

(1) Define the learner $L = \{L_1, L_2, L_3, \cdots, L_K\}$, K stands for the number of learners, and L_k stands for the k th learner, where $1 \le k \le K$.

(2) Define the learner ability level $A = \{A_1, A_2, A_3, \cdots, A_K\}$, and A_k represents the learner's L_k , where $1 \le k \le K$. And satisfies $\sum_{q=1}^{4} e_q = 1$.

(3) Kolb learning styles are divided into four types: divergent thinking, absorption, convergent thinking, and adaptive, so define the learning style of K learners $LS = \{ls_1, ls_2, ls_3, \cdots, ls_k\}$, ls_k represents the style type to which the k rd learner belongs, $ls_k = \{ls_{k1}, ls_{k2}, ls_{k3}, ls_{k4}\}$, where ls_{k1} indicates the matching value of the learner belonging to the divergent thinking type, and the matching value of ls_{k2} is the matching value of the learner belonging to the absorbent type, ls_{k3} The matching value of the learner belongs to the convergence thinking type, and ls_{k4} the learner belongs to the matching value of the adaptive type.

(4) Define the learner's target knowledge point $H = \{H_1, H_2, H_3, \cdots, H_K\}$, where H_k denotes the k th learner's target knowledge point, and each H_k has M binary values, then $H_k = \{h_k 1, h_{k2}, h_{k3}, \cdots, h_{kM}\}$, $1 \le k \le K, 1 \le m \le M$, and if $h_{km} = 1$, the m th knowledge point of the k th learner is the target knowledge point, otherwise $h_{km} = 0$.

(5) Lt is the time period in which the learner wants to master the target knowledge point, $Lt\_l \le Lt \le Lt\_u$, where Lt_l is the minimum value of the target time and Lt_u is the maximum value of the target time.

2.2.2. Learning Resource Model

(1) Define the learning resource $S = \{S_1, S_2, S_3, \cdots, S_N\}$, and S_n denotes the first n th learning resource, where $1 \le n \le N$. The learning resource that the learner starts to learn is ns_i , and the next learning resource that the learner will learn is ns_j .

(2) Define the knowledge points $U = \{U_1, U_2, U_3, \cdots, U_M\}$, and U_m denotes the m th knowledge point. Each U_m has N learning resources corresponding to it, then $U_m = \{U_{m1}, U_{m2}, U_{m3}, \cdots, U_{mN}\}$, when U_{mn} denotes the difference in the difference between the learning of the first m knowledge point and the corresponding learning resources value, $1 \le n \le N, 1 \le m \le M$.

(3) Define the degree of difficulty of the learning resources $D = \{D_1, D_2, D_3, \cdots, D_N\}$, where D_n

represents the degree of difficulty of the n th learning resource, and the degree of difficulty of ns_i is D_{nsi}, ns_j has difficulty level D_{mj}.

(4) Learning resource time information $T = \{T_1, T_2, T_3, \cdots, T_N\}$, T_n denotes the time consumed in learning the n th learning resource.

(5) The media types of learning resources include various types such as text, video, audio, image, interactive learning software, etc. Therefore, the media type is defined as $MT = \{mt_1, mt_2, mt_3, \cdots, mt_N\}$, mt_n the n th learning resource The type of resource attributed, $mt_n = \{mt_{n1}, mt_{n2}, mt_{n3}, mt_{n4}\}$, where $mt_{n1}, mt_{n2}, mt_{n3}, mt_{n4}$ denotes respectively the matching values of the learning resources with the four modalities of text, symbols (graphs, animations, etc.), video (audio), and interactive software expressions, and with $\sum_{q=1}^{Q} mt_{nq} = 1$.

2.2.3. Decision-Making Variables

Define the personalized learning path variables as the matrix $X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NN} \end{bmatrix}$, if there is a path between the i th learning resource to the j th learning resource, then $x_{ij} = 1$, otherwise $x_{ij} = 0$. Define the sequence relationship between learning resources as:

$$S_{ij} = \begin{cases} 1, & \text{Learning resource } i \text{ is the preorder relation of } j \\ 3, & \text{Learning resource } i \text{ is the postorder relation of } j \\ 2, & \text{Learning resources } i \text{ and } j \text{ are in a parallel relationship} \end{cases} \tag{3}$$

2.2.4. Construction of the Objective Function

According to the above construction of the learner and learning resource model, the mapping relationship between the two is established, and the following objective function for personalized learning path construction is formed.

(1) The learner cognitive level function, which reflects the difference between the learner's current level of learning ability and the degree of difficulty of its learning resources. It is expressed as follows:

$$F_1 = \sum_{j=1}^{N} \left| \frac{\sum_{i=1}^{N} \left[X_{ij}(D_{nsi} - A_k) + X_{ij}(D_{nsj} - A_k) \right]}{2\sum_{i=1}^{N} X_{ij}} \right| \tag{4}$$

(2) A learning style function that represents the difference between a learner's learning style and the type of learning resource medium. It is represented as follows:

$$F_2 = \frac{\sum_{n=1}^{N} \sum_{q=1}^{Q} X_{ij} \,|\, ls_{kq} - mt_{nq} \,|}{X_{ij}} \tag{5}$$

(3) The desired target expenditure function, which represents the matching value between the learner's target knowledge points and their corresponding learning resources, as well as the sequential relationship between the learning resources. It is expressed as follows:

$$F_3 = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} X_{ij} U_{mn} H_{km} S_{ij}}{X_{ij}} \tag{6}$$

(4) A time constraint function that represents the difference between the length of time the learner wants to learn and the time needed to complete the learning resource. It is expressed as follows:

$$F_4 = (\max(t\_l_k - \sum_{n=1}^{N} t_n X_{ij}, 0)) + (\max(0, \sum_{n=1}^{N} t_n X_{ij} - t\_u_k)) \tag{7}$$

Above is the objective function for the learner model and the learning resource model representation, because each objective function has a different degree of influence on the learner, so its corresponding weight is different, this paper for the four sub-functions using the weight of 0.2, 0.2, 0.3, 0.3, respectively. The total objective function is as:

$$\min F(x) = \sum_{i=1}^{4} w_i F_i \tag{8}$$

The objective function is the minimum value of the solution problem, which can ultimately find a set of optimal decision variables in the solution space, that is, the learner's learning path. The learner's spending on the learning path is its corresponding objective function value, so when the value of the objective function is smaller, the learner spends less on the path, and therefore the generated personalized learning path is more in line with the learner's requirements.

2.3. Learning Path Solving Based on Dynamic Content Optimization Algorithm

Taking the learner model, knowledge point model, and generic learning path as inputs, the improved genetic algorithm above is used to design a personalized learning path construction framework.

2.3.1. Framework for Personalized Learning Path Construction

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 implementation process is shown in Figure 3.

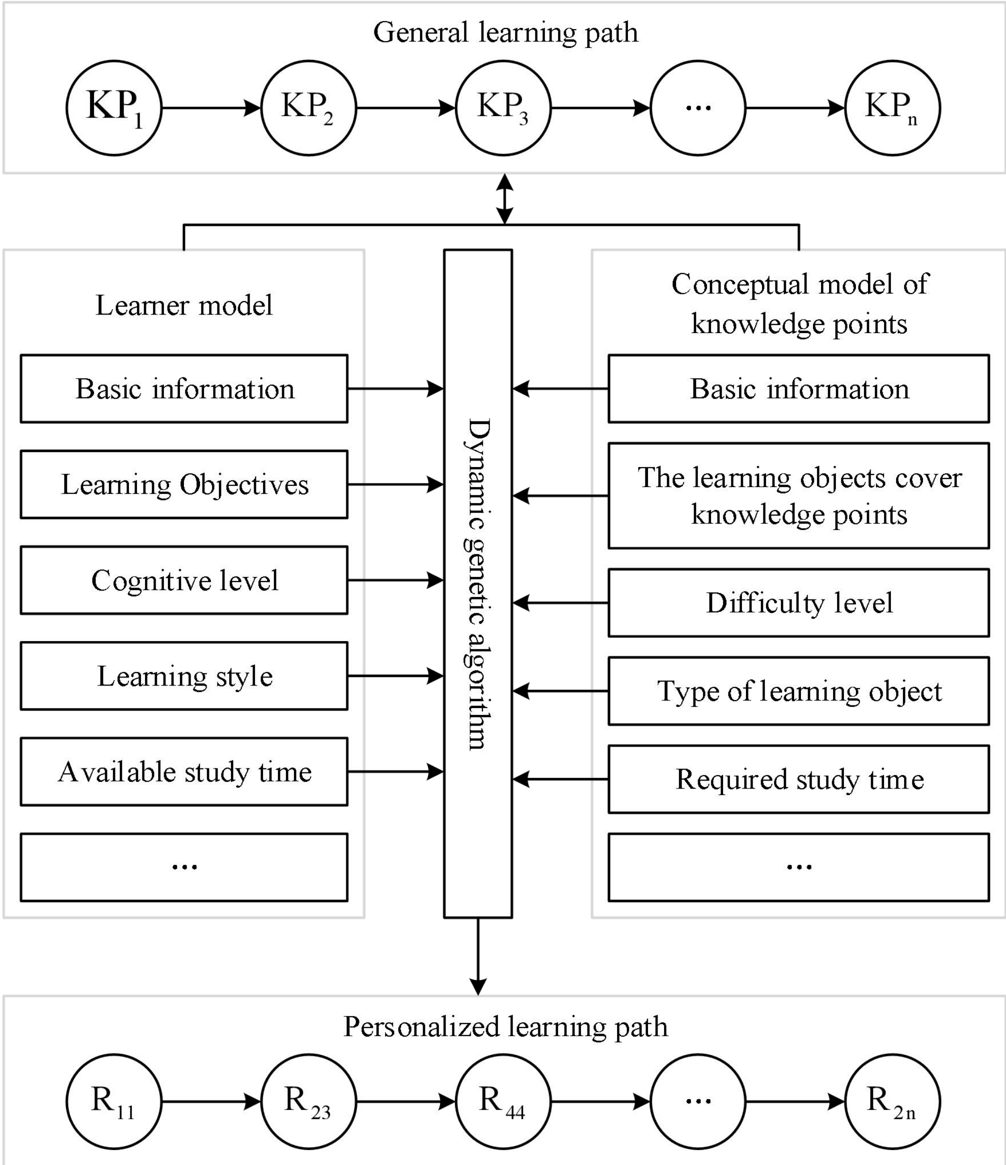

Figure 3. Framework for Constructing Personalized learning Paths.

2.3.2. Solving the Personalized Learning Path Construction Problem

The main implementation steps of the multi-adaptive dynamic 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 $CS=(C_1,C_2,\dots C_n)$. Let each concept C_i in CS include m types of learning objects, but only one learning object R_i can be used to construct the learning path, and the parameters can be encoded accordingly. An individual presented with R_{ij} is denoted as the i th type of learning object in the j th knowledge point. In this study, the selection of learning objects is determined by learner characteristics.

(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 is kept constant 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.

(3) Fitness evaluation: after initialization, the fitness function evaluates the fitness value of each individual to determine the fitness between the learning object and the learner's features, and selects the better individual as the parent 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 $KP_{pr} = (MC_n, MS_n, DL_n, MT_n)$, the fitness function is given in Eq:

$$f = \sum_{i=1}^{4} (wi \times fi(L_{pr}, KP_{pr})) \tag{9}$$

where: wi represents the weight of the fitness function, which is applicable to adjust the proportion of fi , and the importance of the fitness function can be determined by adjusting the corresponding weight, and fi represents the number of participations in the adaptation between learner characteristics and knowledge point characteristics. The smaller the value of the fitness function $f1$, the more the constructed learning paths are in accordance with the learner characteristics. The four objective functions considered in the fitness function are described above.

(4) Selection operator: this study adopts a tournament selection strategy to select individuals, and in order to prevent the problem of one or a few candidate solutions with extremely high fitness always occupying the whole population during the iteration process, leading to the problem of missing diversity, we consider to collect the individuals that are not selected in the selection stage to form a set of non-elite individuals, which will be kept separately to participate in the iteration process. In each iteration, the non-elite individuals will replace the duplicate individuals that appeared in the selection stage, which ensures that the best individuals can be selected to enter the progeny and also enriches the population diversity.

(5) Crossover operator: a single-point crossover method is used, in which every two consecutive individuals are treated as parents, a crossover point is randomly selected, and reproduction is carried out by exchanging the coding of the crossover points at the corresponding positions of the two parents. The operation of the crossover operator in this study is different from the methods used in general genetic algorithms, and two crossover scenarios are considered in the crossover process because the set of non-elite individuals is collected. One, crossover is performed in pairs between all individuals in the current population. Two, crossover in pairs between the current population and random individuals in the set of non-elite individuals with the aim of increasing the diversity of the population.

(6) Variation operator: the use of variation operator is a random search of the candidate solution space in order to avoid the problem of creating a local optimum and to create diversity by making random changes to individuals. The variation method designed in this study is to use other types of learning objects in the same knowledge point to replace the original type of learning objects.

(7) Termination condition: all individuals are evaluated according to the fitness function, and high-quality individuals are retained to participate in the iteration in order to make the algorithm converge until a predetermined number of iterations is reached.

3. Results and Analysis

This section provides a comparative analysis of the performance of personalized learning path generation based on dynamic content optimization algorithms and evaluates the practical application effects of the generated personalized learning paths. Based on the application effect of personalized learning paths, the study proposes the following hypotheses:

Research hypothesis 1: Personalized learning paths can improve learners' academic performance.

Research Hypothesis 2: Personalized learning paths can effectively reduce learners' study time.

Research hypothesis 3: Personalized learning path can stimulate learners' interest and increase their motivation.

Algorithm simulation programming platform is Matlab R2014b and operating system is MacOS. Hardware environment is intel Core processor i5 with 2.60GHz and 16GB of RAM.

3.1. Performance Evaluation Based on Dynamic Content Optimization Algorithm

With the above personalized learning path model as the core, the dynamic genetic algorithm based on multiple adaptations in this paper is utilized, while the classical genetic algorithm (GA), differential evolution (DE) algorithm and whale optimization (WOA) are selected for personalized learning path optimization, respectively. In order to verify the optimization effect of different optimization methods, the personalized learning path optimization problem is set up and the path generation performance of each method is evaluated using demand adaptation. The convergence diagram of the algorithms can clearly show the optimization process of each algorithm, and the optimization performance of each core algorithm can be observed through the comparison of the optimization process. Figure 4 shows the convergence curve of the objective function under each algorithm.

By comparing the convergence curve of the mean value of the total optimization function adaptation under different numbers of knowledge points, it can be seen that the algorithm in this paper has the best convergence speed and convergence stability, and the objective function can converge to about 12 in 140 iterations of the model. The comparison algorithm needs more than 150 iterations to complete the convergence, and the convergence value of the objective function is higher than this paper's algorithm. It shows that in the case of the same number of knowledge points, the personalized learning path optimized using this paper's algorithm is more in line with the needs of the learner, showing better optimization speed and matching degree.

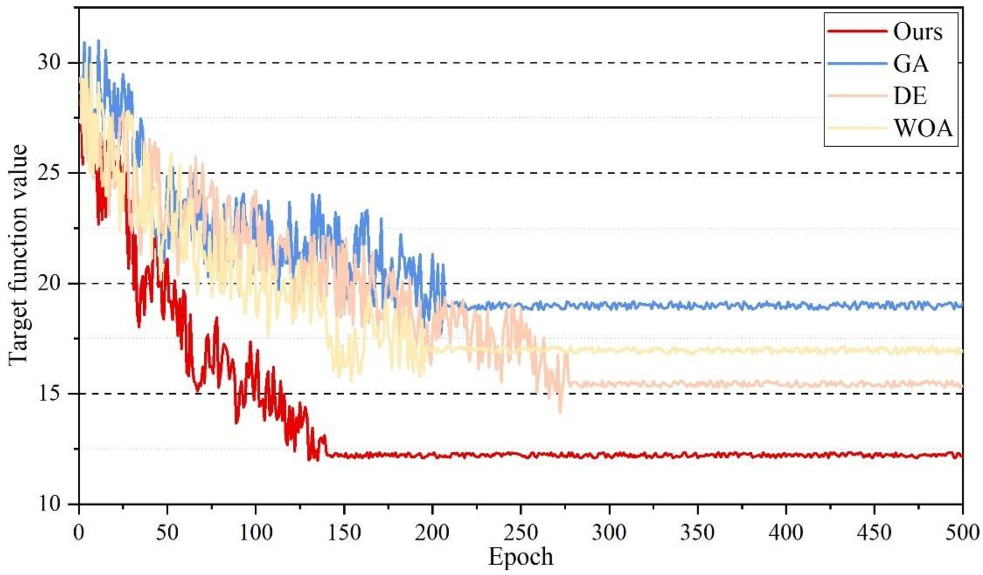

Figure 4. The target function of each algorithm is the curve of convergence.

Based on the personalized learning path construction process designed above, simulation experiments of personalized learning path generation are conducted. The classical genetic algorithm (GA), differential evolution (DE) algorithm and whale optimization (WOA) algorithm are also selected for learning path generation comparison experiments. The parameters of each algorithm in the experiment use the same setting scheme. Meanwhile resource saturation is simulated using random values. The optimization process of each algorithm is limited to 10 iterations due to the small size of the resources set in the experiment. The two algorithms address 3 different learning needs, i.e., knowledge, understanding, and mastery of the knowledge points. Separately, 20 independent experiments are conducted to record the optimal adaptation value and the worst adaptation value of the path, and then the average adaptation value is measured. The results of the learning path adaptation experiments generated by each algorithm are shown in Table 1.

From the perspective of the adaptation values of the paths generated by the simulation experiments, the adaptation values of the learning paths obtained by this paper's algorithms under different needs are higher than those of the comparison algorithms, and the average adaptation values under the needs of cognition, comprehension, and mastery are 2.480, 3.328, and 3.714, which is improved by 7.55%~75.02% compared with the comparison algorithms. It indicates that the algorithm in this paper generates learning paths with matching adaptations under the three different needs of learners, which improves the personalized needs of mobile learning paths to a certain extent.

Table 1. The algorithm generates the learning path fitness results.

Demand		Ours	GA	DE	WOA
Cognition	Max	2.626	1.826	1.936	2.424
	Min	2.355	1.294	1.242	2.234
	Average	2.480	1.418	1.417	2.306
Understand	Max	3.495	2.538	2.538	3.124
	Min	3.231	1.842	1.787	2.773
	Average	3.328	2.187	2.067	2.923
Master	Max	3.801	2.971	2.862	3.421
	Min	3.645	2.517	2.366	3.108
	Average	3.714	2.676	2.605	3.292

3.2. Example Analysis of Personalized Learning Path Application

3.2.1. Comparison of Changes in Academic Performance Before and After Application

A total of 60 students in the second year of undergraduate study in a university were invited to participate in this experiment to compare the changes in learners' knowledge mastery ability after the recommendation of personalized learning paths. The learners were evenly divided into 2 groups according to the pre-test scores, each group of 30 learners, all of which contained learners with different cognitive levels.Learners in group A were the experimental group, who followed the method designed in this paper to carry out personalized learning paths to learn on the short video platform.Learners in group B were the control group, who followed the conventional way of learning to learn on the short video platform.

The distribution of the pre-test and post-test scores of the two groups of learners is shown in Figure 5. It can be seen that in the pre-test stage, the average score of each group is 71.1 and 71.17 respectively, and the significance coefficient of the t-test is P=0.975>0.05, which indicates that the two groups have similar scores, with no significant difference, and there are learners with different levels of cognitive ability. After the personalized learning path recommendation stage of learning, the cognitive ability of the learners have different degrees of improvement. Among them, the average of the posttest of the experimental group compared with the pre-test stage increased from 71.17 to 79.73, with a more obvious improvement effect. While the average score of the posttest of the control group only increased by 1.16 points, indicating that the personalized learning path constructed based on the dynamic content optimization algorithm can effectively improve the cognitive ability of the learners. Meanwhile, in the posttest stage, the average score of the experimental group is 7.4 points higher than that of the control group, and the significance coefficient of the t-test, P=0.017<0.05, indicates that there is a significant difference in the cognitive level between the two groups. The experimental results show that the personalized learning path can significantly improve the cognitive level of learners, so hypothesis 1 is proved.

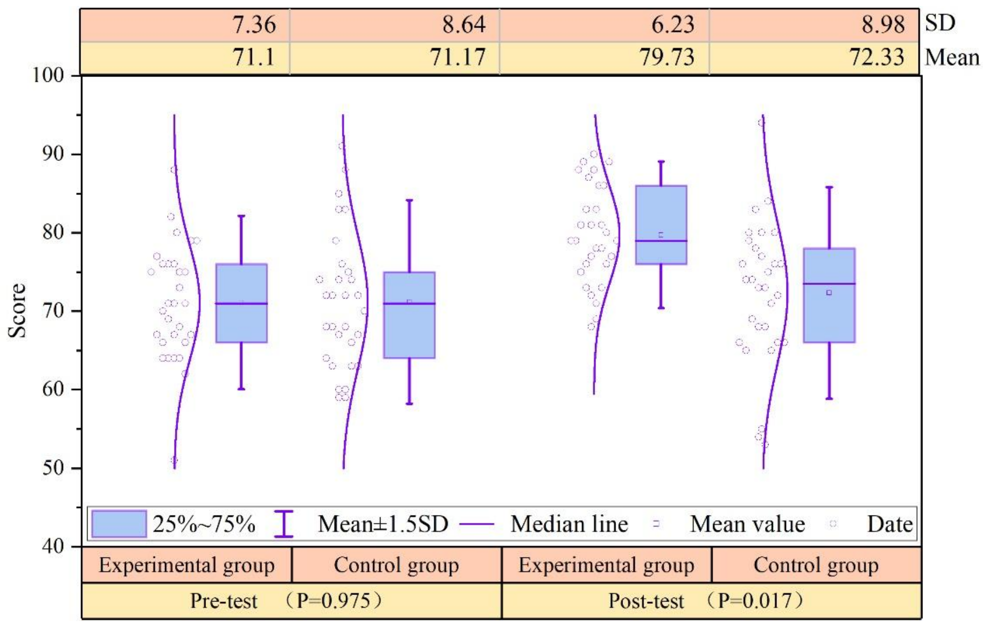

Figure 5. Two groups of learners' pre-test and post-test performance distribution.

3.2.2. Impact of Personalized Learning Paths on Learning Time

At the end of the learning process, collecting the student learning time data recorded in the log of the short video platform, the average learning time of the two groups of students learning each knowledge point can be calculated, and the results of the comparison of the average learning time of the two groups are obtained as shown in Figure 6.

As can be seen from the figure, for most of the knowledge points, the time used by the students in the experimental group is obviously shorter than that of the students in the control group, and the average learning time of the students in the experimental group is 65.36 min, while the average learning time of the students in the control group is more than 80 min. this is because when the students in the experimental group learn according to the recommended personalized learning path, the students do not have to spend time on searching and selecting resources, and can spend more time is spent on learning, and the time utilization is more efficient. However, some students are special, such as student 5 in the experimental group, whose average time to learn all knowledge points is 79.83 min, which is higher than that of the general control group students. This is because for some students in the experimental group, although the learning path is given, due to their own poor learning ability. While some students in the control group have strong learning ability and can also find suitable learning resources for themselves. Secondly, there is a large gap in the learning time of the students in the control group, while the time used by the students in the experimental group is relatively stable. This is because the students in the control group have different abilities to search for resources, different learning abilities, and different time to find suitable resources for themselves. In the experimental group, the resources were determined according to students' learning styles and cognitive abilities, which could better meet students' needs. However, due to the different learning abilities of students, there is a certain gap in learning time, but it is still relatively stable compared to the control group.

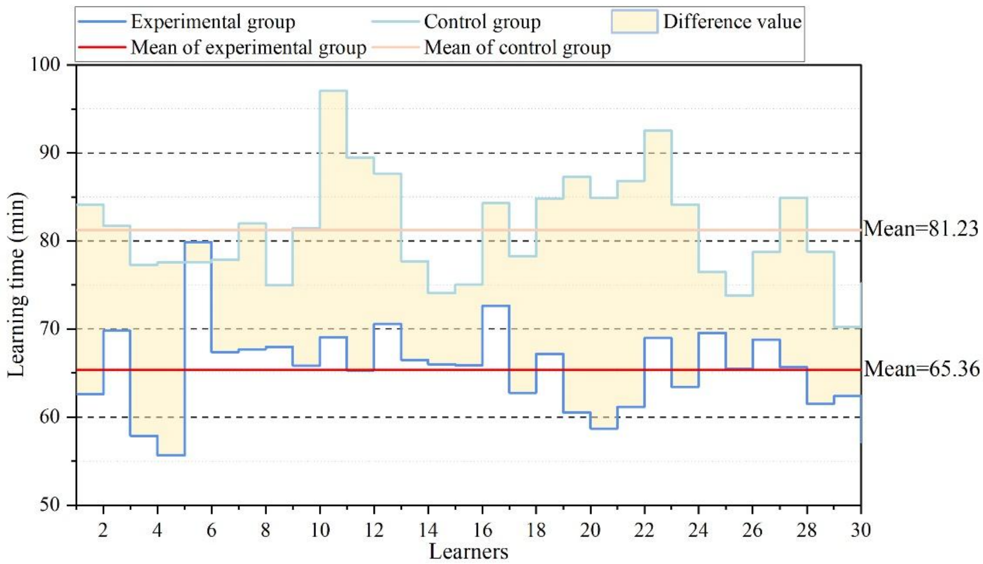

Figure 6. The average study time comparison results.

In order to further verify that it is plausible that there is a significant difference between the two groups of students in the average study time, the study uses SPSS data analysis software to test the study time data. With the grouping category as the grouping variable and the study hours as the test variable, the independent samples t-test was used to compare the differences between the two groups, firstly to determine whether the data conformed to the normal distribution, and then to execute the independent samples t-test, and the results of the analysis of the differences in the study hours are shown in Table 2.

Where the Sig value of the Leneve test of the variance equation is significantly greater than 0.10, the results of equal variances are taken, and vice versa, the results of unequal variances are taken. In terms of learning time, the Sig value of the Leneve test of the variance equation is 0.117, then the result of equal variances is taken, which means that the significance value of the difference of the t-test is 0.007<0.05. It shows that it is plausible that there is a significant difference between the students of the experimental group and those of the control group in terms of the average learning time, and it indicates that the students of the experimental group, with the support of the individualized learning paths, have mitigated the information disorientation and cognitive loading phenomenon and effectively save learning time. Therefore, the average learning time of students learning according to the personalized learning path is significantly lower than that of traditional learning. Therefore, hypothesis 2 of the study is considered to be valid.

Table 2. Learning time difference analysis results.

<table>
<tr><td colspan="3" rowspan="2"></td><td colspan="2">Learning length</td></tr>
<tr><td>Equal variance</td><td>Variance not equal</td></tr>
<tr><td rowspan="2">Levene testing</td><td colspan="2">F</td><td>3.152</td><td></td></tr>
<tr><td colspan="2">Sig.</td><td>0.117</td><td></td></tr>
<tr><td rowspan="7">t test of the mean equation</td><td colspan="2">t</td><td>16.449</td><td>16.135</td></tr>
<tr><td colspan="2">df</td><td>118.271</td><td>116.554</td></tr>
<tr><td colspan="2">Sig. (Double measurement)</td><td>0.007</td><td>0.002</td></tr>
<tr><td colspan="2">Mean difference</td><td>9.348</td><td>9.103</td></tr>
<tr><td colspan="2">Standard error value</td><td>0.435</td><td>0.535</td></tr>
<tr><td rowspan="2">95%CI</td><td>Lower limit</td><td>6.371</td><td>6.629</td></tr>
<tr><td>Upper limit</td><td>8.429</td><td>8.537</td></tr>
</table>

3.2.3. Learning Path Application Satisfaction Survey

In order to verify the effectiveness of the learning personalized learning path constructed in this paper, the personalized learning path based on the dynamic content optimization algorithm is put into the actual teaching, and the time applied to the actual teaching is 12 weeks in total. Mainly through the questionnaire survey of students, the questionnaire survey mainly includes two aspects of learning path analysis and student satisfaction survey.

The survey questions about the learning path setting are as follows:

A1: The learning path meets the cognitive level.

A2: The learning path can improve the learning efficiency.

A3: The order of knowledge points in this learning path is reasonable.

A4: The learning path is better than the traditional path.

A5: The learning path will continue to be chosen.

The survey questions about the student satisfaction settings are as follows:

B1: This learning path increases the interest in learning.

B2: The learning path meets individualized needs.

B3: The learning path enhances independent learning.

B4: The learning mode is better than traditional learning mode.

B5: Will continue to choose this mode of learning.

The questionnaire uses a five-level Likert scale to investigate the learning path analysis and student satisfaction, that is, there are 5 options under each of the above questions, which are "strongly agree", "agree", "general", "disagree" and "strongly disagree". Students can fill in the information truthfully according to their personal psychological feelings, and there is no right or wrong answer. A total of 30 questionnaires were distributed this time, and the effective rate was 100%. SPSS25.0 was selected to analyze the data this time, and according to the data results, the following will analyze the students' satisfaction with the difficulty of the designed resources and the presentation of the resources.

Figure 7 presents the results of the personalized learning path design survey. By analyzing the data, it can be seen that the path design meets the cognitive level of the students and the students want to continue to choose this path for learning has a high mean value, and the average score of each question is between 4.12 and 4.72. It shows that the design of the pathway is in line with the cognitive load level of the students, and the planning of the pathway is correct and reasonable for the students. The mean value of the path's knowledge points in a reasonable order (A3) is 4.42, which is higher than that of the learning path is in line with the cognitive level (A1) and that the learning path improves the learning efficiency (A2), which indicates that it is a gradual process in terms of the difficulty of the knowledge and that there is coherence between the knowledge. For learning efficiency (A2), the mean value is 4.12, which is on the low side, indicating that there are still deficiencies in this learning process and further improvement is needed.

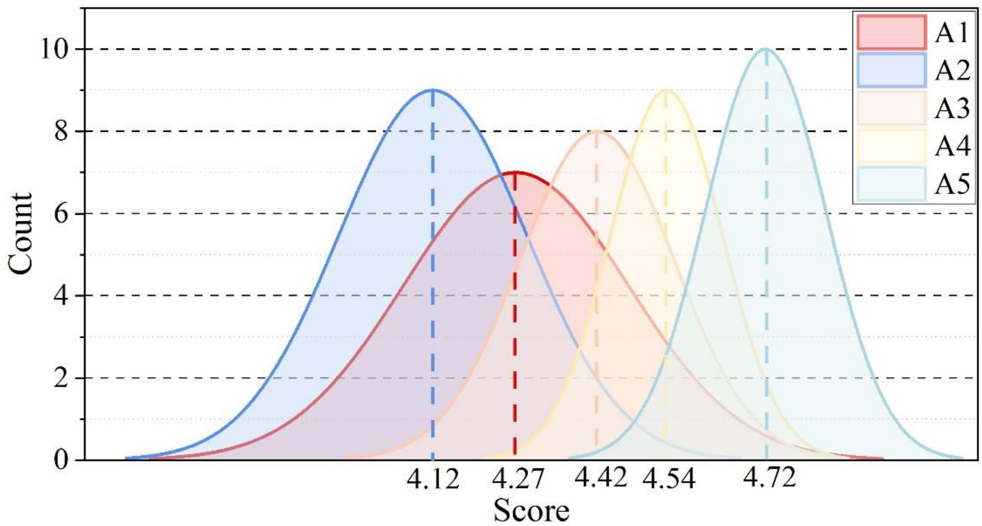

Figure 7. Study path design results.

The main purpose of the survey on the satisfaction of the learning model based on the personalized learning path is to find out whether the model provides students with learning resources that meet the cognitive load level and the construction of the resource presentation form during the learning process, so as to enable students to have a better satisfaction of adaptive learning.

The results of the student satisfaction survey are shown in Figure 8. Through the analysis of the survey data, the average scores of this learning method has increased the interest in learning (B1) and will continue to choose this learning method (B5) are 4.51 and 4.62, respectively, which can be seen from the data that the students' interest in learning increases in the process of adaptive learning. And students preferred the learning style based on personalized learning path compared to the traditional teaching style. The mean value of this learning path enhances independent learning ability (B3), this learning path meets individualized needs (B2), and this learning path is better compared to traditional learning path (B4) is higher. It indicates that in the learning process, the learning style under the personalized learning path can better meet students' individualized needs than the traditional linear teaching method, thus promoting effective learning. In contrast, the lowest mean value of 4.20 for this learning approach to enhance independent learning ability (B3) indicates that the internalization of knowledge is carried out through human-computer interaction in the adaptive learning process. It is possible that just exposed to the personalized learning path recommendation, students' independent and autonomous learning problem solving ability is not enough, but overall the satisfaction of adaptive learning is high. In summary, therefore, hypothesis 3 is considered to be valid.

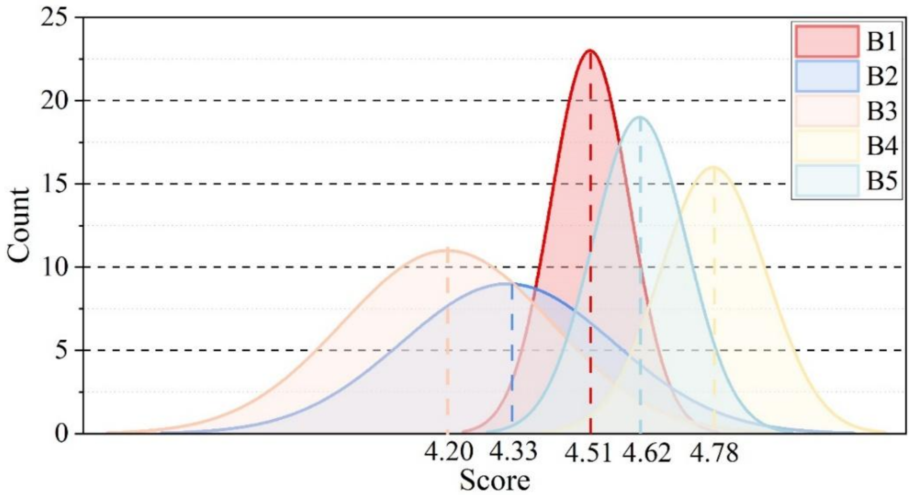

Figure 8. Student satisfaction survey results.

4. Conclusion

In this paper, an improved genetic algorithm based on dynamic content optimization is designed, and the overall flow of the algorithm is given. By constructing the learner model and learning material model in the personalized learning path, the mapping relationship between them is established, and the objective function of personalized learning path construction is formed. The improved genetic algorithm is used to solve the personalized learning path construction problem, which includes seven core steps, such as parameter coding, initializing population, and adaptation evaluation. The performance of personalized learning path generation is evaluated through algorithm comparison, and the method of this paper is applied to a university to further evaluate the practical value of personalized learning path. The mean value of adaptation of this paper's algorithm for generating learning paths according to learners' needs ranges from 2.480 to 3.714, which is 7.55% to 75.02% higher than other methods. Personalized learning paths significantly improved the performance of the experimental group, with the mean score increasing from 71.17 to 79.73, while the control group's increase was only 1.16 points. The personalized learning path recommended to shorten the knowledge learning time, and the average time for students in the experimental group to learn the knowledge points was 65.36 min, while the average learning time for students in the control group was 81.23 min. For the learning mode under the personalized learning path, the mean value of the students' satisfaction in all evaluation dimensions was more than 4.20 points, which improved the students' interest and motivation in learning.

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