Research Article

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Blended teaching design of UMU interactive learning platform for cultivating students' cultural literacy

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Abstract: With the growth of informatization in education and the need to enhance comprehensive national strength, it is important to promote students' autonomous learning ability and cultural literacy. Blended teaching (BT) is also a new way that meets the teaching reform and the context of the times. To improve teaching efficiency, a BT design model for Beijing Youmu Technology Co., Ltd (UMU) interactive learning platform (ILP) that integrates genetic algorithm (GA) is investigated. Simulated annealing algorithm is embedded on traditional GA, and the teaching design model is experimentally tested. The results showed that the maximum value of the optimal fitness of the improved GA was 0.94 and the minimum value was 0.92, which were 0.04 and 0.2 higher than the traditional GA, respectively. The minimum value of the average fitness of the improved GA was 0.86 and the maximum value was 0.94, which were 0.15 and 0.12 higher than the traditional GA, respectively. When the initial population size was 150, the performance was best and the computation time was shortest. After BT, the average score of the experimental class increased by 6.33 and the standard deviation decreased to 4.93. The research results indicate that the BT design of the studied UMU ILP has an improvement effect on teaching efficiency and has certain application potential in the field of BT.

Keywords: instructional design, BT, GA, UMU interactive learning platform, SAA

1 Introduction

In recent years, the country has made great efforts to cultivate national cultural literacy and promote innovation ability. With the advancement of time and technology, the informatization of education has played an important role in promoting lifelong learning for all [1]. Traditional teaching relies on communication between teachers and students. Although the teacher-directed teaching model can fully play the leading role of teachers, the passive reception of knowledge neglects the promotion of students' innovation and autonomy. The traditional mode of teaching cannot always meet the requirements of developing culturally literate talents. In order to develop talents who can meet the demands of modern society, it is necessary to reform traditional education and focus on forming students' independent learning ability and innovation consciousness. Genetic algorithm (GA) is an easy-to-implement and efficient global search algorithm derived from computer simulation of natural biological features [2,3]. However, traditional GA tends to get stuck in local solutions, leading to problems of non-standard and inaccurate coding. In addition, traditional GAs still have problems with premature convergence and low operational efficiency, so they are often not used in isolation. Simulated annealing algorithm (SAA) is derived from the principle of solid state annealing, which searches for the best solution by the solid state falling from high temperature to low temperature [4]. The research on embedding SAA into traditional GA for optimization is to promote the convergence ability and global optimization ability of the algorithm. The Beijing Youmu Technology Co., Ltd (UMU) interactive learning platform (ILP) is based on an online platform and has various teaching functions, which can enhance the interactivity and fun of teaching. The innovative use of various teaching functions based on online platforms has significantly enhanced the interactivity and fun of teaching. Online platforms not only provide a massive amount of learning resources, but also offer diverse learning methods, such as video explanations, virtual experiments, interactive Q&A, etc., providing students with a richer and more vivid learning experience. These diverse learning resources help to broaden students' knowledge horizons and enhance their cultural literacy.

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One major advantage of online learning is that it can be conducted anytime, anywhere, allowing students to utilize fragmented time for learning, improving the efficiency of time utilization. Offline learning, on the other hand, can enhance students' practical abilities through practical operations, and the combination of the two enables students to master knowledge more comprehensively. The ILP can also provide personalized learning paths and recommendation systems based on the learning situation of students. This enables students to learn according to their own interests and needs, improving their learning interest and effectiveness. In addition, online learning can also break geographical restrictions. Students can communicate and collaborate with people from different places, which can enhance their communication and teamwork abilities, and further enhance their cultural literacy. Finally, ILPs can also provide real-time learning feedback, helping students discover and correct errors in a timely manner, and improving their learning outcomes. This timely feedback mechanism helps students better grasp knowledge, and improve their learning efficiency and outcomes. The blended teaching (BT) design of UMU ILP with GA is to optimize learning efficiency and improve the students' cultural competence. The research content consists of four main parts. The second part is a review of the current research status of instructional design and GAs at home and abroad. The third part is a BT design based on cultivating students' cultural literacy. First part constructs a BT design model for the UMU ILP, and the second part designs an improved GA. The third part is a practical research on BT on the UMU ILP. The results indicated that the hybrid teaching design of UMU ILP for cultivating students' cultural literacy had good application effects.

2 Related works

At present, online education on online platforms is one of the key areas of education reform both domestically and internationally. The BT design based on traditional education and online education has attracted the attention of many professionals. Among them, research on instructional design has achieved many results. To improve the learning autonomy of nursing students, Logan et al. introduced a self-regulated e-learning module into their instructional design by using self-regulated learning theory. The results showed that the program was helpful in improving the learning initiative of nursing students [5]. Marek and other scholars believed that the research on developing new instructional designs due to the transformation of face-to-face courses into online courses is of great significance. Researchers investigated this through open-ended questions and provided statistical surveys. The research results indicated that as a part of their career development, it was important for teachers to develop teaching plans that were suitable for the current social background [6]. Pellas's research team believed that it is significant to use immersive virtual reality (VR) to instructional design. The study proposed a teaching design strategy model based on VR support and provided quantitative data for analyzing visual design features of different learning subjects. The results indicated that the strategy model was beneficial for enhancing students' learning interest and performance [7]. Whittle et al. designed an instructional design framework to address urgent remote learning environments. This design adopted a participatory design approach and identified several disciplinary areas and design themes. The results indicated that the design scheme could effectively deal with unplanned remote teaching situations [8]. Narvekar and other scholars proposed to apply transfer learning to reinforcement learning and designed a reinforcement learning instructional design model to solve the problem of difficult interaction between reinforcement learning and real scenes. This method could use the learning experience gained in the previous learning task, and investigate and classify the current curriculum. The results showed that this method was feasible [9].

Applications of GAs support research in blended instructional design. Shanmugasundaram et al. developed a one-way road network design model using GAs to optimize the distance travelled by vehicles in road network design. This model introduced a branch and bound technique that could perform breadth first search. The experimental results showed that this scheme could calculate the shortest travel distance and effectively reduce the total distance travelled by vehicles [10]. Researchers such as Velliangiri proposed a solution to improve task scheduling in cloud computing by utilizing the blended search function of GAs, considering the importance of cloud computing in the internet field. This scheme finds the global optimal solution taking the advantages of GA and electronic search algorithm. The results showed that the performance of this scheme was superior to existing cloud computing optimization algorithms [11]. Vivekanandam et al. believed that data preprocessing was very important in model recognition. To develop a high-precision and high-efficiency data preprocessing model, an adaptive blended GA detection method was designed using GA. The test results indicated that this method had superior performance in practical verification [12]. Sun et al. proposed an automatic convolutional neural network architecture design scheme using GAs to efficiently solve image classification tasks in convolutional neural networks, and compared this scheme with other algorithms. The comparison results showed that this scheme outperformed other architecture design algorithms in terms of classification accuracy and resource consumption [13]. Ince scholars have recognized the importance of automated intelligent content visualization in deep learning and developed a system based on GA. It used GA to segment the image into panoramic image instances, and then used these image instances to produce new images. The results indicated that the visualization system designed in this scheme could effectively enhance visual content [14]. Ouyang et al. recognized the importance of applying artificial intelligence (AI) in education and studied the empirical evidence of its application in higher education. It was found that AI can predict learning status, recommend resources, and improve the learning experience. The current situation is that traditional AI technologies are widely used, but more advanced AI technologies still lack application implementation [15]. In the personalized learning plan of UMU, several specific teaching methods and strategies have been implemented to improve student participation and learning outcomes: (1) Core goal design, learning framework design, and learning experience design: Ensure that teaching activities are closely integrated with learning support, and focus on optimizing student learning experience. (2) Blended learning structure: Integrating online and offline teaching elements, making the course content comprehensively cover the three major sections of pre class, in class, and post class, providing a flexible learning time frame, diverse learning resources, and an autonomous learning atmosphere. (3) A fully functional network platform: Utilizing the UMU ILP to achieve the integration of online and offline teaching, facilitating interaction and resource sharing. (4) Course creation and learning interaction: Enable teachers to create and manage courses on the platform, as well as implement various learning interaction activities. (5) Learning communities and live learning: Establish learning communities, conduct live learning activities, strengthen community awareness and instant interaction. (6) Multiple access methods: Support various intelligent terminal software access, simplify learning and participation steps through access codes or QR codes. (7) Interactive learning activities: Stimulate students' enthusiasm through various methods such as lottery, games, questionnaire surveys, and discussions. (8) Integration and release of learning materials: Teachers can use the platform to integrate and release learning resources, design learning tasks, and enable students to complete independent learning before and after online class. (9) Targeted Q&A and task assignment: Use the platform to answer students' questions, publish learning tasks, and help students consolidate their knowledge. (10) Transformation of classroom mode: Transforming the traditional teacher centered classroom into a student-centered interactive classroom, increasing interaction between students and teachers, and enhancing student learning motivation. (11) After class tutoring and homework management: Use the platform to publish homework, track students' completion status, and provide personalized tutoring support. (12) Creating learning scenarios and real-time feedback: Teachers create learning scenarios through a combination of offline teaching and online platforms, providing real-time feedback and answering questions. The UMU ILP addresses the challenges of cultural literacy teaching in blended learning environments mainly by integrating the advantages of traditional and online teaching, thereby solving the limitations of student classroom learning time and space, and improving student autonomy in learning. The blended learning model is based on students' learning interests, guiding them to learn independently, and serves as a core goal-oriented learning design model to improve teaching effectiveness. By integrating the advantages of online and offline teaching design, the UMU platform effectively addresses the challenge of creating a balance between online and offline activities and adapting to various learning styles. Schiff and other researchers recognized the value of AI in the field of education, studied the current status of AI education, and evaluated AI tutoring systems and AI educational agents. It was found that AI technology can simulate teacher skills and provide strong support for student development [16].

In conclusion, blended instructional design models that integrate online and offline methodologies are still extremely uncommon, despite the fact that numerous previous scholars and scientists have offered numerous instructional design models for online education research. In this context, GA offers significant potential application value. Therefore, based on the improvement of GAs, the study aims to construct a BT design for cultural literacy-oriented UMU ILP to achieve better teaching results.

3 BT design based on cultivating students' cultural literacy

GA is the premise and foundation of all subsequent research in this article. The focus of this chapter is to introduce the role of GA in testing teaching effectiveness and to make appropriate improvements based on the traditional GA. At the same time, a hybrid instructional design model was developed for the UMU ILP was designed based on the UMU ILP.

3.1 UMU ILP BT design model

The traditional teaching model is that teachers are responsible for imparting knowledge, and students understand and absorb the knowledge imparted. It is challenging for students to establish the habit of active thinking when they are passively receiving information, which prevents them from developing their ability to apply and transfer knowledge. Knowledge that is not flexibly applied is also readily lost. Under the advancement of the technology, educational informatization has also become more mature, and teaching models are not limited to traditional teaching. The UMU ILP is one of the online learning platforms in China [17]. To better cultivate students' cultural literacy, the UMU ILP's BT model integrates the benefits of traditional teaching and online teaching. This not only solves the limitations of students' classroom learning time and space, but also enhances their autonomy in learning. To enhance students' autonomy, it needs to enhance their interest in learning. The design model of BT, which focuses on guiding students' autonomous learning with interest as its core goal, is shown in Figure 1.

The three core elements of the BT design model are core goal design, learning scaffolding design, and learning experience design [18]. BT design covers both online and offline teaching. The course content includes three major sections: pre class, post class, and in class. This plan has the advantages of flexible learning time, diverse learning resources, and autonomous learning atmosphere [19]. To accomplish the natural fusion of offline and online learning, BT design must rely on an intuitive and highly functional network platform. The UMU ILP is a learning platform designed specifically for BT because of its potent features and robust interactivity. The UMU ILP contains a number of functional parts that can accommodate different learning needs, including course creation, learning interaction, learning community, live learning, and learning management [20]. The UMU ILP supports access to various intelligent terminal software. Learning interaction can be carried out through access codes or QR codes, making the operation very convenient.

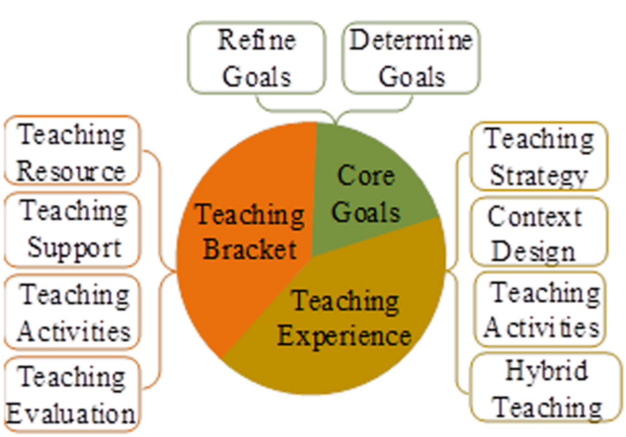

Figure 1: BT design model.

3.2 Online BT design based on UMU ILP

The UMU ILP can interact through various methods such as lottery, games, questionnaires, and discussions to enhance students' enthusiasm. The classroom mode of online teaching structure combined with UMU ILP is shown in Figure 2.

In Figure 2, students can rely on the UMU ILP to do independent learning online before and after class, and can access a variety of course materials. Teachers can also use the UMU interactive platform to provide targeted questions and answers to students and to publish learning assignments. The advantage of BT is that it transforms the teacher-centered classroom into a student-centered classroom, enhancing communication between students and teachers and fully mobilizing students' enthusiasm for learning. By exploiting the advantages of the UMU ILP and combining the framework of the BT design model, a BT design model based on the UMU ILP has been developed in Figure 3.

The BT design model of UMU ILP is mainly divided into three main contents: pre class, during class, and after class. Before class, teachers and students can use the UMU ILP to interact. It helps teachers to integrate learning materials, release learning tasks, and grasp students' learning dynamics. Students can flexibly and independently learn, engage in learning problem discussions, and so on. Students can use the platform for interaction, learning resources, and offline cooperative learning while teachers use offline teaching in conjunction with UMU ILP to carry out instruction. This allows teachers to create learning situations, increase classroom interaction, provide instant feedback, and answer questions. After class teachers can use the UMU ILP to publish homework, grasp the completion status of homework, and provide personalized tutoring, thereby helping students better remember and consolidate the knowledge points they have learned. The teaching method of the UMU ILP BT design model helps to improve classroom teaching, increase learning interactivity, and enhance students' understanding and extension of knowledge points. The UMU ILP adopts the following mechanisms to provide a personalized learning experience

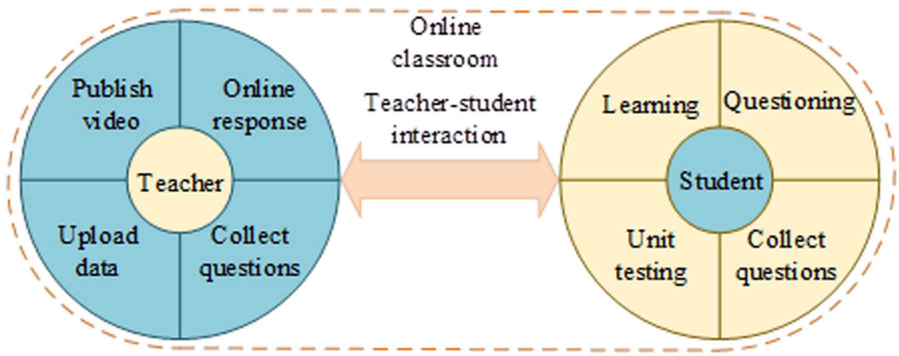

Figure 2: Online teaching classroom model.

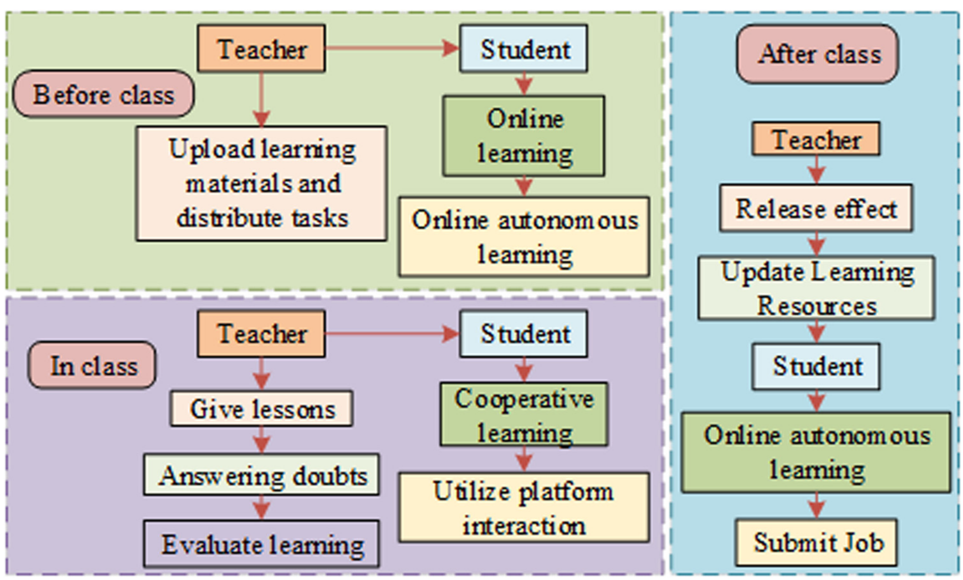

Figure 3: UMU ILP.

and respond to the specific needs and preferences of each student: (1) Personalized tutoring: Teachers can use the UMU ILP to post homework, track student completion status, and provide personalized tutoring and support. (2) Student-centered classroom model: The blended learning model transforms the classroom from a traditional teacher-centered learning environment to a student-centered learning environment, thereby enhancing interaction between students and teachers and stimulating student learning enthusiasm. (3) Interactive learning function: The platform includes functions that facilitate interactive learning, such as lottery, games, questionnaires, and discussions. Such activities can not only increase the fun of the course, but can also be adjusted based on student feedback to better adapt to their learning preferences. Through this approach, UMU ILP is committed to meeting the needs of different learning styles and actively adapting to personalized learning preferences of students. The mechanism by which UMU's personalized learning program measures student success and provides feedback, including the verification of teaching effectiveness, is an extremely important part of its blended learning design. The test results can intuitively reflect the mastery of student knowledge points, and such feedback helps teachers adjust their teaching plans in a timely manner. In addition, utilizing the characteristics of GAs, the UMU ILP can quickly and accurately select question types suitable for course objectives from a large number of question banks, which may be a way for students to measure their performance and progress in the learning process. This feedback and adjustment process supports the educational development of students and promotes their continuous learning and growth. Integrating the UMU platform into the existing learning and teaching framework of educational institutions can be achieved through the following strategies: (1) Teacher training: Providing teachers with training on familiarizing themselves with and using the UMU platform, helping them understand how to use this tool in existing courses. (2) Modify course design: Integrate the functions and objectives of the UMU platform into the course design, making it a part of teaching. (3) Student participation: By introducing the UMU platform to students, let them know how this tool can help them improve their learning.

The UMU ILP uses various multimedia and interactive components to enhance students' learning experience, including lottery, games, questionnaires, and discussions for teaching interaction. These methods can effectively enhance students' enthusiasm. Through this interactivity and diversity, learning platforms encourage students to actively participate in course content and promote their cultural exploration. This teaching method helps to create a more attractive and dynamic learning environment, allowing students to better immerse themselves in learning, thereby improving the overall quality of learning. The UMU International Learning Program has a positive impact on the development of students' cultural literacy through a blended learning design model. This model has improved students' ability to understand and appreciate various cultures, and their cultural literacy has been improved to a certain extent during the learning process. This indicates that UMU ILP is effective in supporting students' understanding and appreciation of different cultures.

3.3 Improving the design of GA

Teaching effectiveness testing is a very important part of the BT design of the UMU ILP. It can provide intuitive feedback on students' mastery of knowledge items, helping teachers to adjust their teaching plans in a timely manner [21]. By exploiting the characteristics of GAs, it is possible to quickly and accurately extract question types suitable for course objectives from a large question bank. GA is a search algorithm proposed based on the evolutionary characteristics of organisms in nature. It can obtain the optimal solution by simulating biological evolution, and is widely used in combinatorial optimization, global solution, and other fields [22]. The inspiration of GA comes from gene selection, crossover, and mutation, which is suitable for finding the optimal solution of multiple combinations. The flow chart is shown in Figure 4.

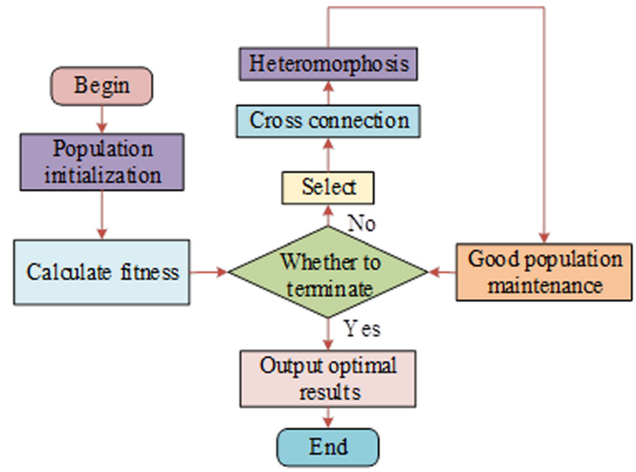

Figure 4: GA flowchart.

In Figure 4, at the beginning, a set of chromosomes is randomly generated as the initial population, and the fitness value of chromosomes is calculated. After selection, crossover, and mutation on the initial chromosome, judgment is made, and population iteration is carried out until excellent individuals are selected. It sets the initialization population H to have n individuals; The two chromosomes in the gene are represented by C_1 and C_2. The probabilities of chromosome crossing and variation are expressed as P and M, respectively. There are various methods of chromosome crossing, such as two-point crossing, single-point crossing, and uniform crossing. Excellent individuals can be selected by crossing, as shown in Figure 5.

In Figure 5, single-point crossing refers to a randomly selected group of genes crossing. Two-point crossing refers to the exchange of two points in the gene sequence, and uniform crossing refers to a certain probability of each gene on the gene crossing. The cross expression is shown in equation (1).

$$R = (K + 2\sqrt{k})/3K, \tag{1}$$

where R represents genetic crossover operation, K represents the sum of iterations, and k represents the number of iterations. From the Equation, the value of R increases normally with the number of iterations. The selection operator function is shown in equation (2).

$$F = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)}, \tag{2}$$

where F represents the selection operator, N represents the number of operators, $f(x_i)$ represents the fitness of the ith individual, and the individual selection probability is shown in equation (3).

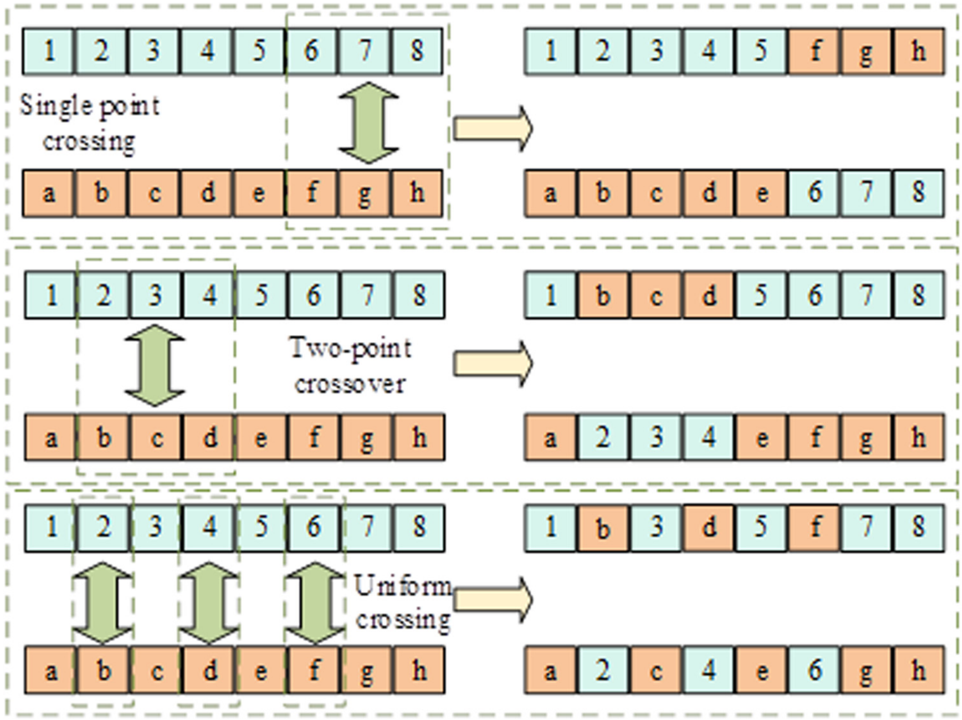

Figure 5: Cross method diagram.

$$P(x_i) = \frac{e^{b\times f(x_i)}}{F}, \tag{3}$$

where P represents the probability of selection, e represents the base of the natural logarithm, and b represents the parameter of control intensity. The larger the value of b, the greater the probability of individuals with high fitness being selected. In the calculation of individual similarity, the population information entropy can be calculated, as shown in equation (4).

$$H(x_i) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{S} p_{ij} \log p_{ij}, \tag{4}$$

where $H(x_1)$ represents the information entropy between individuals. S indicates a total of S alleles that can be selected. p_{ij} represents the probability that the jth allele is K_i, and the similarity between individuals is shown in equation (5).

$$A_{PQ} = \frac{1}{1 + H(x_1)}, \tag{5}$$

where A represents the similarity. The objective function of the GA can be called the fitness function. In the actual solution, the objective function is not negative, as shown in equation (6).

$$\mathrm{Fit}(f(x_i)) = \begin{cases} f(x_i) \\ -f(x_i), \end{cases} \tag{6}$$

where Fit represents the objective function, the function with non-zero constraints is too simple, which will lead to loopholes. The boundary construction method is used for transformation. When the value of the solved objective function is the minimum, the transformation function is shown in equation (7).

$$\mathrm{Fit}(f(x_1)) = \frac{1}{1 + c + f(x_1)}, \quad c \geq 0, c + f(x_1) \gg 0. \tag{7}$$

When the objective function value solved is the maximum value, the transformation function is shown in equation (8).

$$\mathrm{Fit}(f(x_1)) = \frac{1}{1 + c - f(x_1)}, \quad c \geq 0, c - f(x_1) \gg 0. \tag{8}$$

The crossover operator generally uses an invariant crossover probability in the crossover and exchange between parent individuals. Therefore, there is a high probability that the original excellent genes will be destroyed after crossover. It also affects the convergence of the algorithm. To avoid this situation, improvements are made to the crossover operator of the algorithm. Before the crossover operator, it must determine whether or not to perform crossover based on the similarity of the parent generation. The expression for similarity is given by equation (9).

$$S' = \frac{c}{m}, \tag{9}$$

where m represents the coding length of an individual chromosome. c represents the longest length of the same substring between two individuals, and S' represents the similarity between two parents. The cross critical value is shown in equation (10).

$$r = 1 + \frac{g}{G}\Big/3, \tag{10}$$

where r represents the cross critical value, and G represents the goodness of fit. Traditional GA, which has slow convergence speed and poor local search ability, are easy to premature convergence. Simulated annealing reception probability can be used to simulate the annealing of operators after cross-exchange, thereby promoting local search capability. SAA is a probabilistic algorithm derived from the principle of solid cooling annealing. When the temperature is high enough, the solid particles are in a disordered state. As the temperature is gradually lowered, the particles tend to become ordered, avoiding local solutions and eventually finding the global optimum. Therefore, by embedding SAA on the basis of GA, the resulting genetic SAA has better search ability. The SAA is shown in Figure 6.

The genetic SAA is shown in equation (11).

$$P = \begin{cases} \exp\left(-\dfrac{f(x_2) - f(x_3)}{T_t}\right) & f(x_2) \geq f(x_3) \\ 1 & f(x_2) < f(x_3), \end{cases} \tag{11}$$

where T_t represents the temperature at t time. $f(x_2)$ and $f(x_3)$ represent the old and new individuals, respectively. If the new individual is poor, it will iterate according to probability P. If the new individual is better, it will iterate directly. To achieve a condition where the temperature gradually decreases over time, the initial temperature is set to 100°C. The annealing formula is shown in equation (12).

$$T_{1+t} = \tau T_t, \tag{12}$$

where τ represents a constant, usually taken as a fixed value of 0.95, thus obtaining the temperature $T_t = 100 \times 0.95^t$ of the annealing probability at time t. To address the problem of slow convergence speed in GAs, the search interval can be adjusted based on excellent new individuals, thereby reducing search time, as shown in equation (13).

$$\begin{cases} \min f(c_1, c_2, \ldots, c_p) & a_i \leq c_i \leq b_i \\ I_i = \displaystyle\sum_{k=1}^{E} ia(i,k) \cdot 2^{k-1} & i = 1, 2, \ldots, p, \end{cases} \tag{13}$$

where $[a_i, b_i]$ represents the initial search space of c_i, f represents the optimization criterion function, I_i means the number of search steps, E denotes the encoding length of the individual, k represents the value within the $[1, E]$ region. According to the probability selection of the parent, the selection probability of the new individual is shown in equation (14).

$$P(x_i) = F(x_i) / \sum_{i=1}^{n} F(x_i) \quad i = 1 - n. \tag{14}$$

The naming convention table is shown in Table 1.

Based on the detailed design of the system, the actual development of the platform has been studied and completed, and its key functions will be briefly described here.

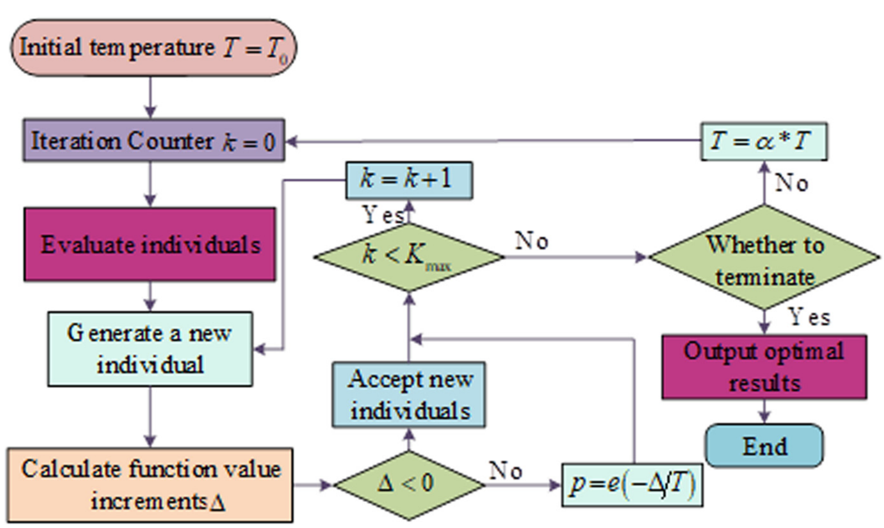

Figure 6: SAA flow.

Table 1: Naming convention table

Symbol	Explain	Symbol	Explain
R	Genetic crossover operation	N	The number of operators
K	The sum of iterations	$f(x_i)$	The fitness of the ith individual
k	The number of iterations	P	Probability of selection
F	Selection operator	e	The base of the natural logarithm
b	Parameter of control intensity	$H(x_1)$	The information entropy between individuals
S	The number of selectable alleles	p_{ij}	Probability that the jth allele is K_i,
A	Similarity	Fit	Objective function
m	Coding length of an individual chromosome	c	The longest length of the same substring between two individuals
S'	Similarity between two parents	r	Cross critical value
G	Goodness of fit	T_t	Temperature at t time
$f(x_2)$	Old individuals	$f(x_3)$	New individual
τ	Constant	$[a_i, b_i]$	The initial search space of c_i
f	Optimization criterion function	I_i	The number of search steps
E	The encoding length of the individual	k	The value within [1,E]

The UMU ILP includes several functional modules to enhance the teaching experience and convenience. These functions include student login, personal information management, viewing course announcements, video teaching, downloading courseware, teaching evaluation, attendance, interactive discussions, and online quizzes. First, introduce the teaching function. The online teaching resources on this platform are classified according to factors such as theme, major, and difficulty, allowing students to easily find and learn educational content that is suitable for their own level based on their learning background. In the student user information interface, students can not only update their basic information, but also set learning parameters, such as knowledge mastery level, acceptable test difficulty, and teaching objectives. These personalized settings will be recorded by the system to provide data support for the process of organizing test papers using GAs, ensuring that the difficulty and exam points of the test papers match the actual learning situation of students. The teacher side provides a question bank interface, which can set parameters such as knowledge point range and question difficulty coefficient. At the same time, set the number of iterations, crossover probability, and mutation probability in the system backend to optimize the algorithm for generating test papers. The system automatically organizes exam papers by combining these parameters and utilizing an improved GA. Before taking the online test paper, teachers need to perform necessary exam management in the management backend. After completing the test paper, the online system will remind users whether the test paper was successfully formed. If successful, students can start answering questions. For objective questions, the system will automatically rate and display the answer results and scores in real-time on the student end. Subjective questions require teachers to manually conduct online review. In addition, after students complete course evaluations and discuss questions, the system will provide message reminders on the teacher's end, making it easier for teachers to respond to student feedback and questions in a timely manner, greatly enhancing teaching interaction and efficiency. Through this meticulous design, the UMU ILP is committed to providing teachers and students with a seamless, efficient, and highly interactive teaching and learning environment.

4 BT practice of UMU ILP

In order to verify the performance of the blended learning design model for the UMU ILP aimed at cultural literacy cultivation, the experimental environment was first configured, and the specific experimental settings are given in Table 2.

To verify the performance of the BT design model of the UMU ILP for cultural literacy, a test experiment was designed. The data required for the experiment was obtained from the UMU ILP. The course "Art and Design Copywriting" was chosen and the regular and experimental classes of the same year were compared. The regular class was taught in the original traditional way, while the experimental class was taught in the UMU ILP's blended learning model. Prior to teaching, the cultural competence of the students in both classes was measured. After the teaching experiment was completed, the students' cultural literacy was measured again in the same way, and the data measured before and after were

Table 2: Specific experimental setup table

Parameter	Value/range	Prove or cite references
Population size	100	Typical population size setting [23]
Cross probability	0.9	Common settings [24]
Mutation probability	0.1	Common settings [24]
Evolutionary algebra	50	Typical setup [25]
Number of runs	50	To obtain statistical reliability [25]

compared for analysis to observe the effectiveness of BT. To compare and verify the performance first, the average and the optimal value of fitness of GA and improved GA were calculated through simulation for comparative analysis, Figure 7.

From Figure 7 (a), the optimal value of fitness of the improved GA was much larger than the optimal value of the traditional GA. The general trend of the two algorithms was that the optimal value of fitness increased as the number of iterations increased. When the iterations of the traditional GA were 50, the optimal value of fitness was 0.72; when the iterations were 450, the optimal value of fitness was 0.9, the highest value. When the iterations were 500, the optimal value of fitness was 0.94, the highest value. The minimum value of fitness of the improved GA was 0.2 higher than that of the traditional GA, and the maximum value of fitness was 0.04 higher than that of the traditional GA, indicating that the improved GA has a better effect on the optimal value of fitness. In Figure 7(b), the AF of the improved GA was also significantly better than that of the traditional GA. The AF of the traditional GA increased with the iterations. The AF of the improved GA increased with the iterations from 50 to 100. The AF remained unchanged from 100 iterations. The minimum value of AF of traditional GA was about 0.71, and the maximum value was 0.82; The minimum value of the AF of the improved GA was about 0.86, and the maximum value was about 0.94. The lowest and highest AF values of the improved GA were 0.15 and 0.12 higher than those of the traditional GA, respectively, indicating that the fitness performance of the improved GA was better than that of the traditional GA.

The Rastigin function and Shubert function were used to examine the performance of both algorithms in order to confirm the search performance of enhanced GA. It set the crossover probability to 0.9, the mutation probability AA to 0.1, the population size to 100, and the evolutionary algebra to 50. Each of the two algorithms was executed 50 times. Table 3 displays the fitness function test results for the two algorithms.

In Table 3, both algorithms can search for the best solution of the function. The improved GA found the optimal solution when the search algebra was 18 and 20, respectively. However, the traditional GA only found the optimal solution when the search algebra was 50 and 48, respectively. The improved GA was significantly superior to traditional GA in search efficiency. The changes in the solution under the $f_1(x, y)$ and $f_2(x, y)$ functions are shown in Figure 8.

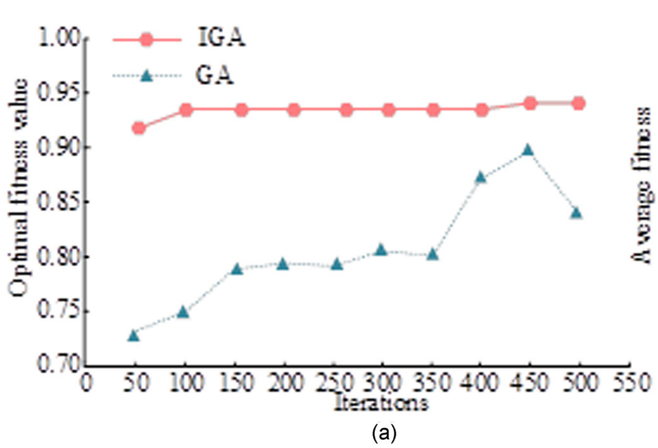

Figure 7: Fitness comparison chart. (a) Comparison chart of optimal fitness values. (b) Comparison chart of average fitness (AF).

Table 3: Comparison chart of optimal results

Test function	Algorithm	Variable x	Variable y	Optimal solution	Optimal algebra
$f_1(x, y)$	GA	1.775	−1.99	3.79	50
	IGA	1.767	−1.99	3.79	18
$f_2(x, y)$	GA	−4.49	−4.53	80.19	48
	IGA	4.54	−4.54	80.19	20

Figure 8 shows that both the traditional GA and the improved GA eventually obtained the optimal solution under different functions. However, the convergence speed of the improved GA was significantly faster than that of the traditional algorithms. The convergence curve of the improved GA was relatively smooth and stable, while the convergence curve of the traditional GA fluctuated greatly and often converged gradually in the later stages of genetic evolution. The variation in the optimal solution under the $f_1(x, y)$ and $f_2(x, y)$ functions is shown in Figure 9.

Figure 9 reflects the variation in the optimal solution under two functions. Comparing Figure 9(a) and (b), the improved GA was almost a straight line and very stable.

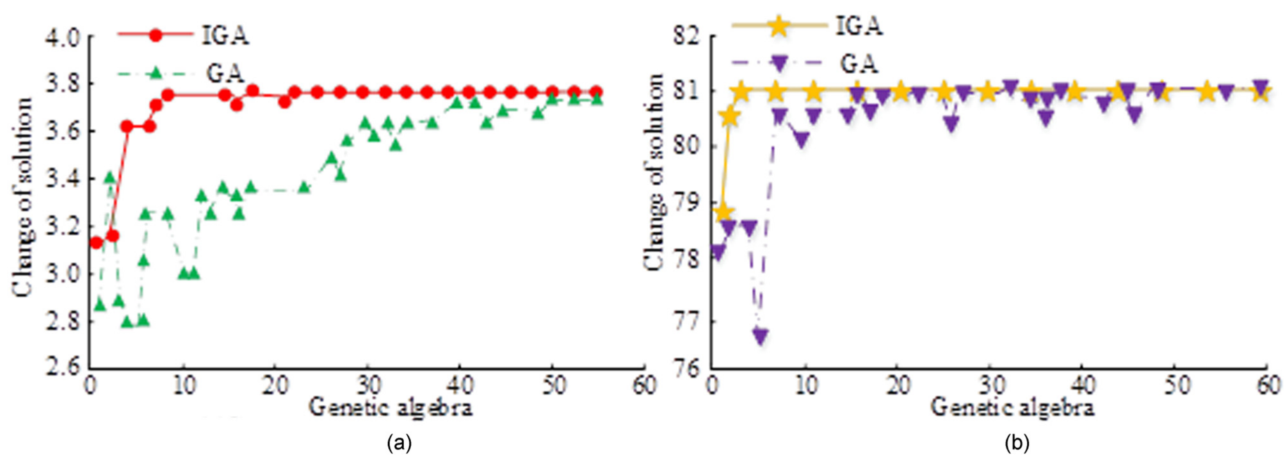

Figure 8: Variation in solution under different functions. (a) Comparison of solution changes under function f_1 (*x*,*y*). (b) Comparison of solution changes under function f_2 (*x*,*y*).

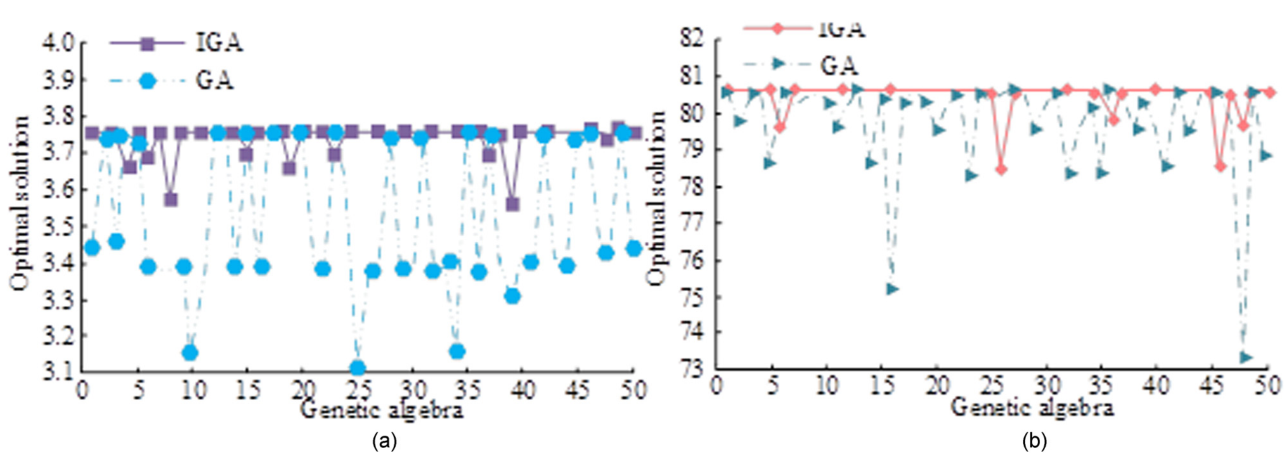

Figure 9: Variation in optimal solution under different functions. (a) Comparison of the best solution changes under function f_1 (*x*, *y*). (b) Comparison of the best solution changes under function f_2 (*x*, *y*).

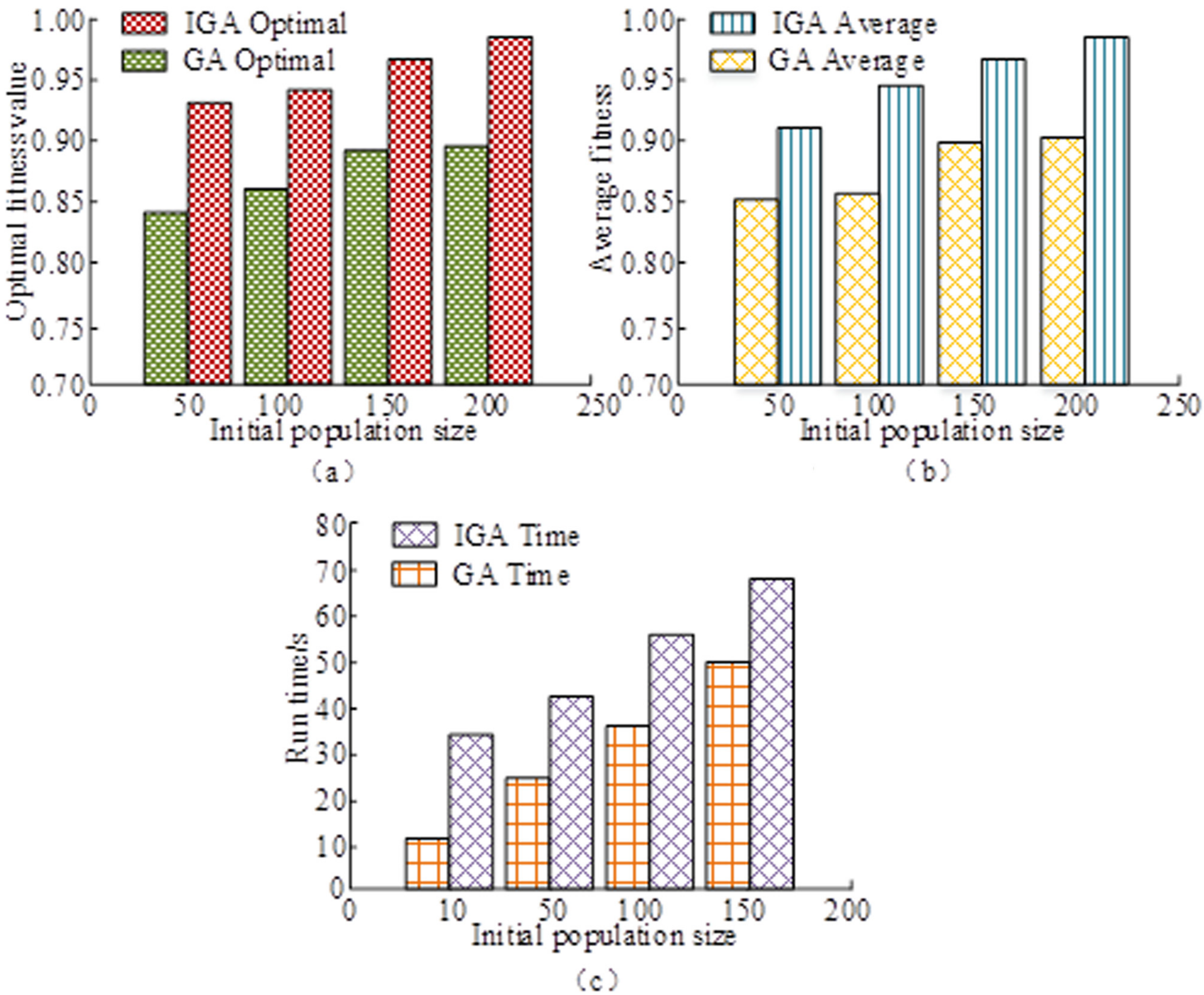

Figure 10: Comparison chart of different population sizes. (a) Operating time of different population sizes. (b) AF of different population sizes. (c) Operating time of different population sizes.

However, the values of the optimal solution in traditional GA varied significantly and irregularly. It can be concluded that the improved GA was also significantly superior to the traditional GA in terms of optimization accuracy and stability. According to the characteristics of the GA, the initial population greatly affected the solution results. To find the optimal initial population, four sets of initial populations with initial population sizes ranging from 50 to 200 were set up for experiments. Under the same parameters and environment, the operation time, AF, and optimal fitness of four groups of initial populations in traditional GA and improved GA were compared, and a comparison chart of different initial population sizes was drawn according to the experimental data, as shown in Figure 10.

Table 4: Comparison of cultural literacy test results

/	Class	Average value	Standard deviation	Mean value of standard deviation and standard error
Before teaching	Regular class	91.78	6.51	1.43
	Experimental class	91.56	5.8	1.4
After teaching	Regular class	93.03	5.71	1.2
	Experimental class	97.89	4.93	1.18

From Figure 10, the larger the initial population, the higher the running time and fitness will increase. Figure 10(a) shows the comparison of the optimal fitness of different population sizes under the traditional GA and the improved GA. From this, the population size has slowed down in the range of 150–200. Figure 10(b) shows the comparison of AF values of different population sizes. From it, the same population size had little change between 150 and 200. From Figure 10(c), the larger the population size, the longer the time it took. According to a thorough review of the data, a population size of 150 had the lowest running time when there was no appreciable performance change, making that number the ideal starting population. The UMU ILP using improved GA first conducted cultural literacy tests on students in both regular and experimental classes before and after teaching. Each class was assigned 150 students, and the cultural literacy test consisted of 30 questions, with a maximum score of 100. The results of the cultural literacy test for both the regular and experimental classes are displayed in Table 4.

In Table 4, before teaching, the results of the students' cultural literacy achievement test in the two classes, which could be used as a teaching control group for the subsequent experimental measurement, were not significantly different. From the post-teaching data, although the cultural literacy achievement test scores of the two classes increased, the rate of increase of the experimental class was obviously higher than that of the ordinary class. The average grade of the regular class increased by 1.25, while the average grade of the experimental class increased by 6.33. At the end of the lessons, the standard deviation of the scores in the experimental class was reduced to 4.93. This indicated that the improvement in students' grades in the experimental class was relatively stable and that the BT design had an overall improving effect on students' grades. In conclusion, learning through the UMU ILP BT design model has a certain improvement effect on students' cultural competence.

5 Conclusion

To better cultivate students' cultural quality and improve teaching efficiency, a BT design model of UMU (ILP) integrating blending inheritance algorithm was designed, and SAA based on traditional GA was embedded for improvement and optimization. The performance test results showed that the minimum value of the optimal fitness value of traditional GA was 0.72, and the maximum value of the optimal fitness value was 0.9. The minimum value of fitness optimal value of improved GA was 0.92, and the maximum value of fitness optimal value was 0.94. The minimum fitness of the improved GA was 0.2 higher than that of the traditional GA, and the maximum fitness was 0.04 higher than that of the traditional GA. The minimum value of the AF of the traditional GA was about 0.71, and the maximum value was 0.82. The minimum value of the AF of the improved GA was about 0.86, and the maximum value was about 0.94. The minimum and maximum AF of the improved GA were 0.15 and 0.12 higher than those of the traditional GA, respectively. When the performance change was not significant, the minimum running time was when the population size was 150, so the most suitable initial population size was 150. In summary, the improved GA outperformed traditional GA in performance. The test results of the teaching experiment showed that the average score of the regular class and the experimental class increased by 1.25 and 6.33, respectively, after the teaching. And the standard deviation of the score of the experimental class was reduced to 4.93. The BT design of the UMU ILP for cultural literacy has an improving effect on teaching efficiency. However, the experimental results are not comprehensive enough due to the limited teaching comparison data and the short teaching time used, and further improvement is needed in this aspect.

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