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Retraction

Retracted: Multimedia Computer-Aided Teaching Platform Based on Particle Swarm Optimization Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] H. Li and Z. Jiang, "Multimedia Computer-Aided Teaching Platform Based on Particle Swarm Optimization Algorithm," *Security and Communication Networks*, vol. 2022, Article ID 1328263, 12 pages, 2022.

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Research Article

Multimedia Computer-Aided Teaching Platform Based on Particle Swarm Optimization Algorithm

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This paper mainly expounds the research hotspots and trends of computer-aided teaching platforms in view of particle swarm optimization algorithm and introduces current situation of computer-aided teaching platforms. This paper analyzes the realization of the core business system of the computer help education platform. And it puts forward the optimization idea of multimedia compute help education platform in view of particle swarm optimization algorithm. The experimental results illustrate Za = 1.42 when students in two classes use the computer-aided teaching platform before optimization. It shows that, at the 0.05 obvious level, there is no important objection in the scores of the two groups of students in the test. When the students in the experimental class used the optimized computer-aided teaching platform, Zb = 3.67, indicating that, at the 0.01 significant level, the performance of the students in the control class was significantly lower than that of the students in the experimental class.

1. Introduction

In the 21st century, society is going through a major new transformation towards the knowledge economy and information age. The rapid development of computer network technology is becoming an increasingly important part of people's life and work. The advent of the information age and the development of computer and network technology have brought new opportunities for the development of Chinese education. Computerized learning platform, a new teaching mode, is gradually being promoted, and computerized learning platform is also receiving more and more attention. The use of learning platforms overcomes the time and space constraints of traditional classrooms. It enables students to learn anytime, anywhere, and repeatedly. It does not have to delay learning because of not listening clearly or forgetting the content, which greatly improves teaching efficiency. At the same time, the learning tool platform can share information resources on a larger scale. It provides students with deeper and more comprehensive learning content, which helps them understand and master new knowledge, expand their thinking space, and stimulate creativity. Therefore, the emergence of computer-aided platforms has subverted the traditional teaching methods, but it has not replaced classroom teaching; it has only become an auxiliary tool to support classroom teaching.

Ant colony algorithm, fish swarm algorithm, and PSO algorithm are typical swarm intelligence optimization algorithms. They are all random optimization algorithms that simulate the behavior of natural biological groups. The advantage of the PSO algorithm is that the algorithm needs to set fewer parameters, and the speed-position update formula is simple and easy to implement. Particles have memory and their convergence speed is fast. The PSO algorithm is an efficient parallel optimization technique, and the PSO algorithm treats each particle as a feasible solution. Each particle is assigned a fit value, which is used to iteratively evaluate and optimize the effectiveness of the particle. There is some room for improvement in the PSO algorithm, which attracts more and more people's attention.

Resources are at the heart of teaching and learning, and managing learning resources presents many problems. The multimedia computer learning platform based on particle swarm optimization algorithm can realize resource storage and rapid creation of online courses, and it supports tens of thousands of users to learn online at the same time. Resources are stored in system files distributed across different storage devices, allowing full utilization of available storage resources. The computing technology of particle swarm optimization algorithm realizes the rapid utilization of resources. It solves the problems of network disconnection and slow mirroring caused by high data concurrency, and it really improves the shortcomings of the e-learning platform in previous years.

2. Related Work

This paper studies some technologies based on the multimedia computer-aided teaching platform of particle swarm optimization algorithm, which can be fully applied to the research in this field. In order to improve diversity and convergence in multiobjective optimization algorithms, Li et al. proposed a multiobjective particle swarm optimization algorithm based on decomposition and differential evolution [1]. Wang et al. believed that the stochastic optimization algorithm based on the population is called particle swarm optimization (PSO), and the group of fish or birds is used as the basis for its intelligent collective behavior [2]. Zhu et al. believed that factors that can influence the construction of a multiobjective particle swarm optimization (MOPSO) algorithm are the leader's decision (global best or personal best) [3]. Liu and Yin believed that the original BP neural network has shortcomings such as slow convergence speed, low accuracy, and being easy to fall into local minimum. So they proposed an improved particle swarm [4]. Yang et al. proposed a method that can improve the distribution and convergence, which is to use the optimization mechanism of particle swarm optimization, based on the multiobjective particle swarm optimization algorithm (MIMOPSO) [5]. Geng et al. believed that particle swarm optimization is poor due to its diversity. It often gets stuck in local optima, leading to premature stagnation. To overcome this deficiency, they proposed an immune particle swarm optimization algorithm based on adaptive search strategy [6]. Bonyadi and Michalewicz studied the motion pattern of particles in particle swarm optimization (PSO) algorithm, and they characterized the motion pattern of particles by two factors [7]. Tharwat et al. proposed a novel disordered particle group majorization (CPSO) arithmetic to majorization of the overmaster integral of Bezier curves. There are two variants of this algorithm: CPSO-I and CPSO-II [8]. Song et al. believed that particle group majorization (PSO) is a promising optimization method in view of the model of bird flocks. This study benefits from the fact that living environment influences flocking behavior of birds [9]. In order to improve the computational efficiency of optimal scheduling of large cascade reservoirs, Wang et al. made full use of the current popular multicore computers. They proposed a coarse-grained side by side adaptive crossbreed particle group majorization algorithm (PAHPSO) [10]. Li et al. believed that particle group majorization (PSO) was a new

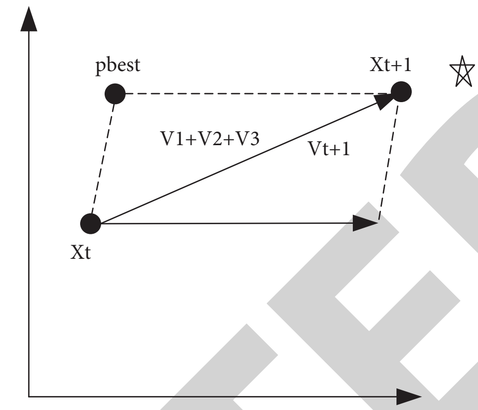

Figure 1: Schematic diagram of particle velocity and position adjustment.

heuristic worldwide to find arithmetic in view of group mind. It discovered the worldwide optimal view in a complicated find interspace by means of contest and collaboration among particles. But PSO is prone to fall into local extrema, premature convergence, or stagnation [11].

3. Method of Computer-Aided Teaching Platform of Particle Swarm Optimization Algorithm

3.1. Particle Swarm Optimization Algorithm. Particle Swarm Optimization (PSO) has been well studied over the past two decades [12, 13]. It is inspired by the group predation movement of birds. In particle swarm optimization algorithm, multiple particles form a swarm. These particles collaborate and are all complementary to attain a certain goal. In the animal kingdom, it may be looking for food; then the location of this food is the target of this suboptimization. The position of each member may be a potential optimal solution. In the process of optimization, each particle can obtain its own historical optimal solution (pbest) through the fitness function calculation and then obtain the global optimal solution (gbest). As the particle positions and velocities are continuously updated, these two solutions are also constantly replaced by better particles. The particle at the global optimal position is the leader of the entire population. All members of the population must keep approaching the leader, so as to find food in the shortest time [14]. The schematic diagram of particle velocity and position adjustment is shown in Figure 1 below.

The target position is the five-pointed star in the figure, and the particles in the figure have velocities in three directions at the iteration time *t*: the speed V3 of the particle itself, the speed V2 of moving to the individual optimal position that it has experienced, and the speed V1 of moving to the global optimal position. Under the combined action of these three velocities, the particles move towards the target point.

PSO algorithm is an iterative optimization algorithm: 1. Initialization of parameters: such as population size, training factor, maximum number of iterations, etc., they randomly

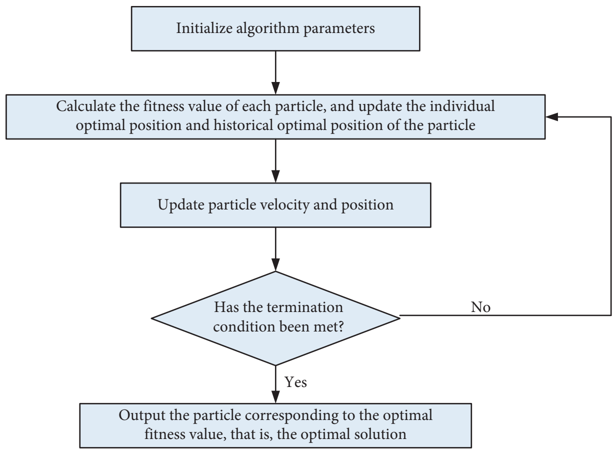

Figure 2: PSO algorithm flowchart.

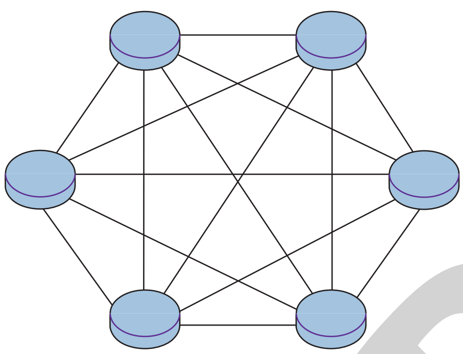

Figure 3: Full connection topology diagram.

generate the initial position and initial speed of particles. 2. Particle estimation: According to the objective function, it determines an appropriate function and then calculates the appropriate value for each particle. 3. Best position update: it updates the individual best position or the historical best position. 4. Updating the population: The velocity and position of the particles are updated. 5. Determining whether the algorithm is over: if the adjustment value no longer changes or the biggest numeral of iterations is achieved, the iteration is terminated; otherwise it returns to step 2. The basic process is shown in Figure 2.

PSO algorithm can be divided into global PSO algorithm and local PSO algorithm. The global PSO algorithm means that the neighborhood of each particle is the entire population, and its social network topology is a fully connected topology. The historical optimal position in the velocity update formula is the optimal position found by the entire population so far, which is called the global optimal position [15]. The optimal information can be quickly transmitted in the whole population, and the convergence speed is relatively fast, but the global PSO algorithm is easy to fall into the local optimum. This is mainly due to the low spatial coverage of particles searched in highly connected social networks. The fully connected topology is shown in Figure 3.

The local PSO algorithm means that the neighborhood of a particle is a part of the particle that is close to it, and its social network topology is a ring topology. Ring topology

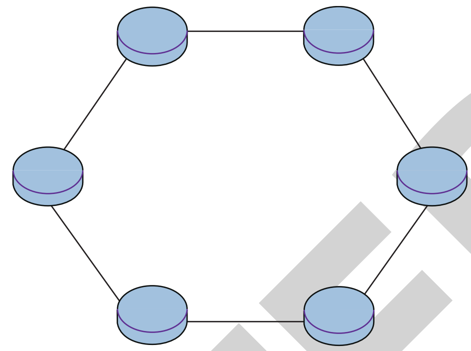

Figure 4: Ring topology diagram.

means that each particle communicates only with Nn particles in its neighborhood, and each particle approaches the best particle in its neighborhood. The neighborhood can be determined by the distance between particles, and the nearest Nn particles are selected as their neighbors. The historical optimal position in the velocity update formula is the optimal position obtained by comparison between the optimal position of the particle itself and the optimal position of the neighborhood, which is called the local optimal position. It reflects local information. Of course, the neighborhoods overlap each other; i.e., a particle can be a neighbor of multiple particles, and they share information with each other. The local PSO algorithm has a slower convergence speed, but the search space coverage is relatively high. When $\mathrm{Nn} = 2$, the ring topology is shown in Figure 4.

The fully connected topology has a fast cautious speed, but it is easy to fall into a local optimum; the ring topology has a slow convergence, but it can search a larger space. Combining these two topologies, the search starts from a ring topology with a minimum number of neighbors, and as the number of iterations increases, the number of neighbors gradually increases until it covers the entire population. Therefore, in the early stage of iteration, the particle can search a larger spatial range. The convergence is accelerated in the late iteration, which reflects the ability of global search and local development [16, 17].

Many problems in everyday life cannot have a single purpose, and the same is true for optimization problems. For example, although the budget given by the customer is very small, the requirements are very large. These two are contradictory. While the quality is improving, the cost and time will definitely increase along with it. Simply put, the multiobjective optimization problem is a process of coordination and sacrifice, that is, optimizing multiple requirements at the same time. The checks and balances between needs are achieved through decision variables. And optimizing one of the goals is carried out on the premise of sacrificing the other goals. Therefore, it is impossible to achieve an optimal solution for a certain target [18, 19]. The vector evaluation genetic method was proposed by a scholar in 1985, and then various multiobjective optimization algorithms were proposed by scholars from various countries. Particle group majorization is a class of swarm-based optimization algorithms, and noninferior solutions are generated at the end of each iteration. Multiobjective particle group majorization (MOPSO) combines the advantages of PSO. For example, with simple operation method, fast convergence speed, etc., it uses PSO to optimize multiobjective problems. For each generation of the population, which particles will become members of the noninferior solution set is determined by the external archive. The motion behavior of the rest of the particles is directed by these noninferior solutions, which are some basic MOPSO principles. The algorithm for forming a population from three subgroups of the same size is called multipopulation MOPSO. The characteristic of the algorithm is that the variation factors used by the three subgroups are not equal, which will improve the search ability of particles. It adopts the PSO of the nondominant permutation method (NSPSO). The archiving method of this method uses the external storage method and then uses the noninferior solution arrangement method when selecting the optimal solution. It combines Pareto dominance and generalized PSO to form a new multiobjective optimization method [20].

Table 1: Psychological research table.

Time delay/acceptance method	2 hours later (%)	7 hours later (%)
Talk (auditory)	71	11
To watch (visually)	73	20
Audiovisual	86	66

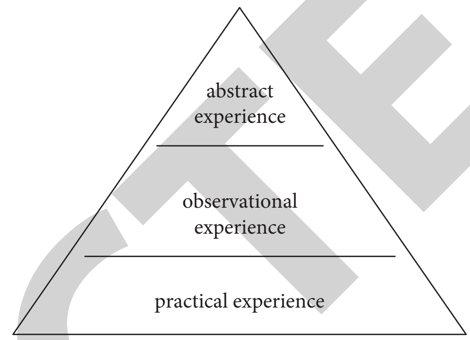

Figure 5: Tower of Experience.

3.2. Multimedia Computer. One aspect of computer-assisted education is computer-assisted instruction (CAI). It refers to the use of computers to help or replace teachers to perform some teaching tasks. It imparts knowledge and provides skills training to students, directly serving students. It integrates various media such as text, graphics, sound, and video. It uses computers to logically connect different types of information and integrate it into interactive learning software [21–24]. It has achieved good results in teaching practice, and it has been recognized in the field of education. Especially under the current conditions in China, Internet-based computer-aided learning has not been widely used, and many technical and practical problems still need to be solved. For this reason, learning resources remain an important teaching tool in universities and colleges, as well as in primary and secondary schools.

The second area is Computer Management Instruction (CMI). It refers to information management and computer systems designed and developed for various purposes to manage and guide the teaching process. It helps teachers prepare for tests and assessments and manage lesson plans and learning resources and more. It directly serves teachers and educational institutions. The question collection system currently in use in some institutions and primary and secondary schools belongs to the CMI. Although CAI and CMI are independent to some extent, they work best when used together. It can upgrade and modify teaching software. The teaching software can be updated and modified in time according to the situation reflected by the CMI, which enables the software and teachers to effectively deal with students' problems and difficulties. It ensures that students master all the content of the course [25].

Early CAI was developed from "program teaching," meaning that students use computers. Through the teaching software-courseware, it can learn autonomously according to the steps of program design. With the development of psychological theory, the connotation of CAI is also changing. According to a broad understanding, any form of computer-assisted teaching can be regarded as computer-assisted teaching. So CAI can be defined as a system that develops computer applications to help educators in teaching, including computer hardware, software, and teaching courseware. The teaching courseware is the core of the CAI system, which represents the connotation of computer-aided teaching. From the perspective of "teaching" and "learning," it can be divided into two basic types: "teaching assistant" and "student assistant." "Teaching assistant type" CAI means that classroom teaching is dominated by teachers. As an auxiliary means, the CAI system replaces the traditional classroom "chalk" and "blackboard," which is also generally called classroom CAI. "Student-aided" CAI means that classroom teaching is student-centered. It learns autonomously through the CAI system, which is also commonly referred to as CAL. This is a personal "CAI."

Information dissemination is a complex process, and several modes of dissemination have been proposed in dissemination theory. Among them, the Bello model is more suitable for the teaching communication process. The Bello model believes that the source, information, channel, and disseminator are the four basic elements in the dissemination of information. The channels include various human sense organs, which reveal the important role of human sense organs in receiving information. Information is primarily perceived through the five senses: sight, hearing, touch, smell, and taste. Among them, vision and hearing account for 94% of the information ingested. From the perspective of the memory effect of receiving information, the psychological research table is shown in Table 1 below.

It can be seen that the visual and auditory senses play a key role in human learning. In teaching, it is spread through the media. Some scholars believe that the media is an extension of the organ. The multimedia computer combines various human sense media, so it can be considered as an

Table 2: Process of multimedia development.

Stage	Stage element	Stage results
Subject selection		
Analyze	Student type analysis Environmental analysis content analysis Target analysis Theoretical empirical analysis	Topic definition
Design	Instructional design software system design Interactive design	Writing textbooks, manuscripts, and flowcharts
Make	Material creation collection Interface design Box media integration	Courseware integration
Evaluation	Run the trial User evaluation Expert evaluation	Revise
Promote the application		

extension of human senses [26]. The multimedia computer integrates and processes information in a multidimensional way, so that the information obtained by different senses of people complements each other. It forms a relatively complete information space, which can enhance students' ability to feel and understand things.

Mathematical knowledge is usually composed of highly abstract language symbols, and students often sound abstract, intangible, and inanimate. The learner's grasp of knowledge has a process from image to abstraction, which brings difficulties to learning knowledge. American psychologists have proposed a hierarchical model for acquiring knowledge. He divided the acquisition of knowledge into 12 levels from concrete to abstract, arranged in a triangle "Tower of Experience." The Tower of Experience is shown in Figure 5 below.

The abstract experience of language signs is at the spire. Direct, concrete practices are located at the bottom of the tower. And the experience of observation is somewhere in between. This means that "experience of observation" has a dual identity; it can be both a bridge from practical experience to abstract experience and the basis of abstract experience. It can acquire abstract knowledge through direct observational learning. However, multimedia computers use images, animations, etc. to vividly express the content, which is suitable for giving full play to the advantages of teaching [27].

Multimedia courseware is the multimedia software used in classroom teaching. Fundamentally speaking, it is still auxiliary teaching, which is a teaching method and cannot replace classroom teaching by itself. For general classroom teaching courseware, it requires developers not only to master the teaching, but also to learn the computer production technology of the courseware. It also needs to understand the process of courseware development. The process of multimedia development is shown in Table 2.

The courseware development process shown in the table above is an indispensable link in actual work, but each link has a different depth, and its courseware will have different effects. Due to the limitation of energy and time in practice, it can be considered according to the specific situation, which link to focus on [28].

3.3. Auxiliary Teaching Platform. Multimedia learning is a form of distance education divided in the light of the development of basic mass media sum message technique, which pertain to the category of 3rd Generation Distance education. Multimedia online teaching is the result of the development of modern Internet and mass production computer technology. Famous Chinese scholars have made a detailed induction and overview of the three information types used in teaching and the stages of the three dynasties of remote learning. The three-generation information technology and three-generation distance education table is shown in Table 3.

From Table 3, we can know that since the 1990s, along with the existence and growth of technology of drug and computer networks and computer multimedia, electronic information sharing technology of double-way interaction has been realized, which makes the teaching process more open and flexible. Therefore, with the advent and lapse of new technologies, media online tutoring emerges as the times require [29].

The emergence of multimedia learning platforms has created a resource-rich research platform for learners. It provides more learning opportunities and a wider source of information for those who wish to acquire knowledge. The advent of e-learning has brought about a new shift in the way of learning. Rather than disseminating knowledge, it places more emphasis on cultivating learners' innovative and practical abilities and at the same time lays a solid foundation for a lifelong learning system. The advent of online multimedia education overcomes the time and space constraints associated with traditional education. It has great space and time advantages, enabling students to learn and explore knowledge not only during class. It not only learns in the classroom, but also has direct contact with teachers. The introduction of multimedia teaching can realize the sharing of teaching resources. Through the multimedia teaching platform, it can optimize the sharing of information and equipment, thereby simplifying the entire teaching process. It better achieves teaching goals.

A web-based learning platform is a complete system software that provides distance learning services. At its core is

Table 3: Three dynasties of technology and three generations of remote learning.

Staging	First generation	Second generation	Third generation
Era	Mid 19th century-mid 20th century	Mid 20th century-late 1980s	1990s to present
Distance learning category	Distance learning instruction	Distance learning for multimedia learning	Distance study with transparency and mobility
Computer software	Traditional printing techniques Postal transportation technique Advanced visual and audio equipment	Based on one-way transmission electronic information telecommunication skills	2-way communication electronic and interactive information systems
Major media	Printed materials, photography, telephone, slideshows, audio recordings	Mass media, personal media, computer-assisted teaching	Advanced telecommunications, radio and wireless mobile networks, digital multimedia

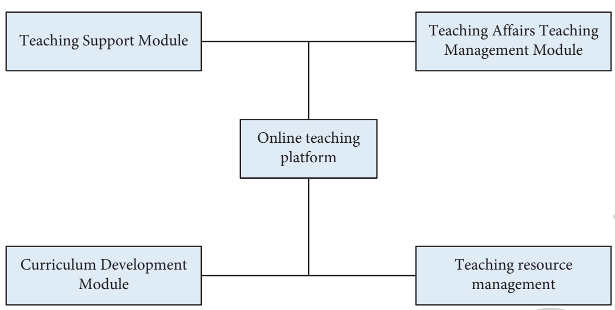

Figure 6: Elements of the online teaching platform.

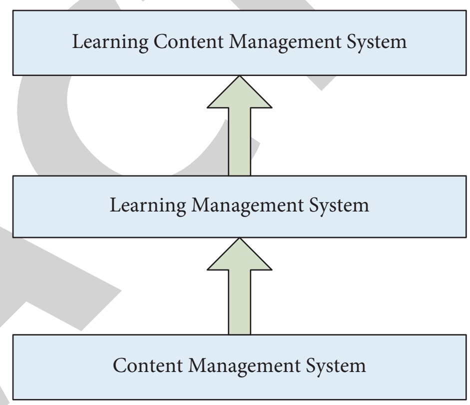

Figure 7: Online learning portal design.

having online learning tools. And it provides services for the full implementation of modern distance education. It uses learning tools in a streamlined and efficient manner. Powered by a learning management system, it integrates online learning tools with the school's distance education services.

A network-based learning platform usually consists of a teaching support module, a teaching management module, a course development module, and a learning resource management module. From another perspective, it can also be composed of an enrollment management module, an online course module, an online assignment module, an online learning module, and an online quiz module. The components of the online teaching platform are shown in Figure 6.

The functions that the teaching support module should have include self-selecting courses, virtual experiments, online examinations, homework grading, guidance and answering questions, and discussions and interactions between teachers and students.

The teaching management module should include functions such as teacher and student registration and certification, student registration management, teacher file management, administrative file management, information reporting and statistical data analysis, subject area management, and course management.

The course development module must complete the task of providing the tools and templates needed to develop an online course.

The resource management module should include a question bank, case studies, resources, and multimedia materials.

Throughout the development history of online learning platforms, it is generally believed that there are three main stages. The development diagram of the online teaching platform is shown in Figure 7 below.

The first stage is the Content Management System (CMS). It is mainly used to store and manage teaching resources. It provides learners with learning resources, focusing on managing learning objects and learning content. In the second stage, the learning management system (LMS) is mainly used to manage administrative affairs and training activities, enabling administrators to manage these activities conveniently. The third stage, Learning Content Management System (LCMS), is a combination the first two phases. It can govern the learning and teaching resources, and it allows administrators and teachers to easily manage and deliver online courses.

Along with the computer web and media skills, next stage of e-learning system evolution will include the features and trends of modernization, transparency, and knowledgeability and customization. Due to the popularity of e-learning platforms, there is an increasing emphasis on developing common standards for these platforms. In order for the platform to be compatible with online courses and learning tools, its development must be related to core standards. The standardization of online learning platforms is the natural trend of its growth. The platform's accessibility ensures the interoperability, intelligence, and personalization of online

Table 4: Comparison of results between AITLBOPAO and PSO and NPSO.

No.	Function	Algorithm	Min	Max	Mean	Std
F1	Sphere	PSO	16.506234	1.6242e + 02	55.571231	25.749857
		NPSO	2.154757	60.737034	17.645351	16.415387
		AITLBOPSO	0.003011	0.152728	0.0565763	0.055508
F2	Schwefel2.21	PSO	8.372365	99.9990	40.072062	34.464859
		NPSO	4.930421	14.272837	8.891716	2.266229
		AITLBOPSO	0.008387	0.070396	0.039247	1.6686e-04
F3	Step	PSO	21.050130	1.3875e + 02	57.852517	28.926104
		NPSO	1.092144	47.952262	16.471155	10.979474
		AITLBOPSO	2.2147e-05	0.484655	0.087966	0.016722
F4	Rosenbrock	PSO	4.4493e + 02	9.4410e + 04	1.0402e + 04	2.3642e + 04
		NPSO	1.2608e + 02	1.1837e + 03	5.0291e + 02	2.6600e + 02
		AITLBOPSO	0.205707	59.732885	20.481599	11.706281
F5	Levy	PSO	2.390605	55.288855	22.779303	11.65354
		NPSO	6.099171	34.476224	15.302917	6.374933
		AITLBOPSO	0.067801	0.609816	0.269633	0.079866
F6	Penalized1	PSO	17.760942	2.0505e + 13	1.2538e + 12	4.2052e + 12
		NPSO	6.602316	43.326210	23.475862	9.612926
		AITLBOPSO	4.2367e-06	0.090833	0.030284	0.17477
F7	Penalized2	PSO	8.3026e + 05	1.1864e + 13	1.2967e + 12	2.5424e + 12
		NPSO	35.118878	1.6198e + 10	1.0042e + 09	3.0863e + 09
		AITLBOPSO	0.004243	0.116102	0.042152	0.020798
F8	Alpine	PSO	3.253283	21.921899	13.335974	4.166173
		NPSO	2.256609	12.216215	5.867291	2.231011
		AITLBOPSO	0.018304	0.046013	0.034057	0.009084

data to meet the individual learning needs of learners and facilitate teachers.

4. Experiment of Computer-Aided Teaching Platform of Particle Swarm Optimization Algorithm

4.1. Experiment of Particle Swarm Optimization. To test its validity AITLBOPSO algorithm, it is compared with particle group majorization (PSO) and exponentially decreasing improved particle group majorization (NPSO). In this paper, 4 unimodal functions and 4 multimodal functions (among which, F1-F4 are 4 functions of single modality; F5-F8 are 4 professions of polymodality) are selected for testing. Each numerical test operation runs 30 loops. It compares Min (minimum), Max (maximum), Mean (average), and Std (variance) of the three algorithms, respectively. The comparison table of the results of AITLBOPAO and PSO and NPSO is shown in Table 4.

From the data comparison in Table 4, it can be seen that AITLBOPSO outperforms PSO and NPSO in terms of Min, Max, Mean, and Std of 8 test functions. The performances of Min, Max, and Mean illustrate that the AITLBOPSO algorithm has no real solution accuracy compared to the PSO and NPSO algorithms. It also has a more prominent performance on both global search and local search. Among them, the Step function, Penalized1 function, and Penalized2 function perform better than the other two algorithms in the Min value, and the solution accuracy is higher than 4 orders of magnitude. In terms of Mean and Std, the AITLBOPSO algorithm performs the best. It shows that the results of each independent test of the AITLBOPSO algorithm are very close, and it has strong stability. In the early stage of iteration, due to the addition of effective information particle swarm algorithm and the convergence trend of AITLBOPSO the experimental results show that the algorithm outperforms the PSO algorithm NPSO. In the middle and late stages of algorithm iteration, due to the addition of teaching and learning optimization algorithms, compared with the PSO algorithm and the NPSO algorithm, the local ability need to search. AITLBOPSO algorithm is still very prominent. It stops the operator fall localized optima. Among them, the Schwefel2.21 function, Penalized1 function, Penalized2 function, and Apline function have shown strong advantages in the early stage of iteration due to the addition of effective information particle swarm optimization. Both convergence speed and downward trend are better than other algorithms. Sphere function, Schwefel2.21 function, Step function, and Penalized1 function are close to the other two algorithms in the solution accuracy in the middle of iteration. In the later stage, due to the addition of the teaching and learning optimization algorithm, the exchange of individual information between the populations is increased, so that the algorithm can jump out of the local optimum in the later stage and search for more feasible regions of the solution space.

4.2. Computer-Aided Experiments. Computer-assisted teaching is a method and technology of various teaching activities under the aid of computer to discuss teaching content, arrange teaching process, and conduct teaching training with students in a dialogue manner. It can generally be divided into three parts: computer hardware, system

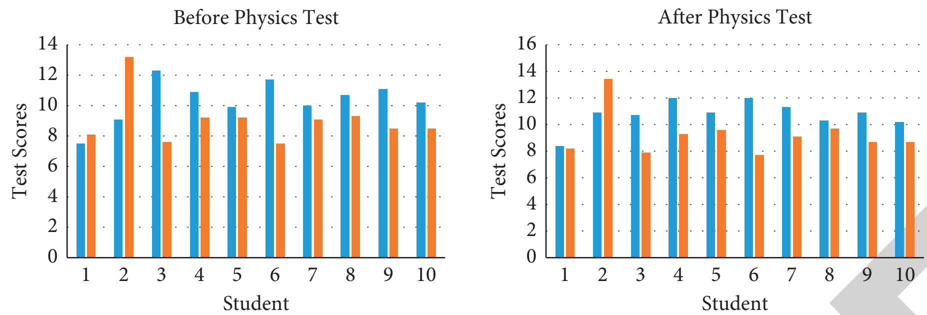

Figure 8: Statistical chart of pre- and posttests of physical inventive minds of pupils in lab with control groups.

software, and course software. Modern educational technology is the application of computer information technology to education and teaching. Multimedia and computer networking applications have grown in popularity since the 1990s. It makes constructivism rise rapidly in the world, and it becomes the latest theoretical basis of modern educational technology. Constructivism holds that knowledge is not acquired through teacher teaching. It is acquired by learners in the construction of meaning through the extensive use of various learning tools (including textbooks, audiovisual materials, multimedia learning tools, software tools and various learning information from the Internet, etc.) in a specific context, that is, in a social and cultural environment and aided by another person, either a tutor or a study buddy, because learning is a process of constructing meaning in a situation with the help of others. That is, through interpersonal collaboration, constructivist learning theory believes that "contextualization," "collaborative learning," and "dialogue interaction" are the most important elements in the learning environment. "Dialogue interaction" is an essential element of the learning environment. Constructivism advocates learner-centered, teacher-led learning. This means that the learner's role as a cognitive subject has been valued, and the teacher's guidance has not been neglected. Teachers are helpers and facilitators of meaning construction, rather than imparting and instilling knowledge. Students are the main body of information processing and active builder of meaning, rather than passive receivers of external stimuli.

In this paper, students from the of lab and core classes high school in a school were selected for the experiment. It sets the marks of lab and test group in the pretest of the physical creative thinking test as variables a and b, respectively. In this paper, the marks of lab and test group in the posttest of the physical creative thinking test are set as c and d, respectively. Since this experiment belongs to a large sample, it adopts an independent double overall Z test. The pre- and posttest statistics of the students' physical creative thinking in the marks of lab and test group are shown in Figure 8 below.

It can be calculated from the data in Figure 8 that $Za = 1.42$, indicating that, at the 0.05 significance level, there is no significant difference in the physical test scores between the students in the experimental class and the students in the control class before the experiment. $Zb = 3.67$, indicating that, at the 0.01 significant level, the pupils in the lab group scored remarkably better than peers in the test group in the physical test after the experiment.

The scores of the students in the pilot and test arms used in mathematical reasoning pretest were defined as variables A and B, respectively. The scores of the students in the pilot and test arms used in mathematical reasoning posttest were defined as variables C and D, respectively. Figure 9 shows the results of the preresults of the pilot and test results of pupils in the control group in the creative thinking of mathematics:

From the data in Figure 9 and the independent double overall Z calculation, $ZA = 1.4$ indicates that, at the 0.05 significance level, no serious variation was found among the students in the experimental class and the students in the control class in the mathematics test before the experiment. $ZB = 4.275$, indicating that, at the 0.01 significant level, the scores of the students in the experimental class in the mathematics test results were remarkably better over the those in the control class after the experiment.

The intuitive visualization of computer-aided teaching provides rich materials for students' image thinking. It contributes to the construction of physical models and mathematical models in students' minds, which provides conditions for the development of creative imagination and intuitive thinking. The high-speed computing function and bitmap simulation function of the multimedia computer can simulate the complex physical change process instantaneously. And it displays its motion process and function image on the screen. It enables students to understand at a glance the difficult and changeable intermediate transient processes and function curves of motion.

4.3. Application of Online Teaching Platform. This paper uses the questionnaire survey method to carry out experiments on the online application of learning portal. The official distribution object of the questionnaire is the college students who have used the online teaching platform of colleges and universities to conduct study events. Among the polled institutes were the following in Jiangxi Province, namely, Nanchang University, Jiangxi Normal University of Science and Technology, and Nanchang Aviation University (hereinafter referred to as Changda, Jiangxi Faculty of Physics and Sciences, and China Southern Airlines). A total of 300 questionnaires were distributed and 288 captured; the

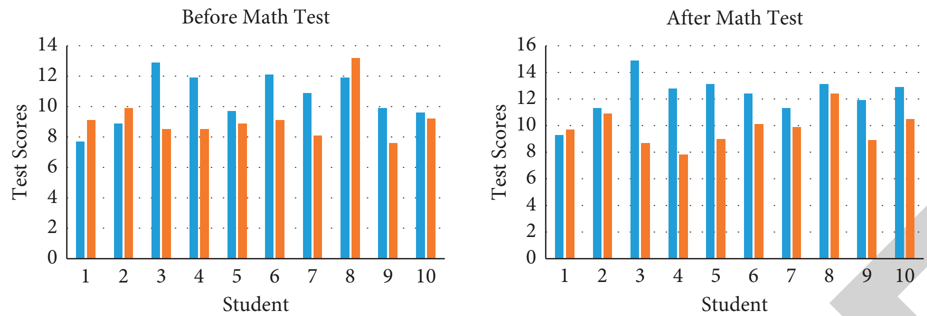

FIGURE 9: Statistical chart of pre- and posttests of mathematical student thinking spirit in lab and control groups.

TABLE 5: Distribution of gender, grade, and major.

Gender			Grade			Profession		
Female	123	52.5%	Freshman Sophomore	111 44	47.3% 19.2%	Liberal arts Science	120 51	51.2% 22.2%
Male	110	47.5%	Junior year Senior year	65 13	27.6% 5.9%	Engineering Other	60 2	25.4% 1.2%

capture rate is 96%. Among them, there were 233 valid questionnaires; the valid fee is 81%. Among them, Nanchang University issued 100 copies and recovered 93 copies, and Jiangxi Province University of Science and Education issued 100 copies and recovered 96 copies. Nanchang Aviation University distributed 100 copies and recovered 99 copies. The basic information of the respondents of the questionnaire includes five aspects: gender, grade, major, the convenience of using computers, and the time spent on the Internet after school. The distribution of gender, grade, and major is shown in Table 5.

It can be seen from the table that, in the selection of the survey samples, the proportion of male and female samples is equal.

It can be seen from the questionnaire that 63% of the students use the computer more conveniently in terms of the convenience of using the computer. And 37% of students think it is inconvenient to use a computer. Through the analysis of these three universities, the number of people who use computers easily in Nanchang University accounts for 87.2% of the total number, followed by Jiangxi University of Science and Technology, and China Southern Airlines is the least. The reason is that the campus network of Nanchang University is more convenient. And it has opened a wireless network in the student dormitory, while the campus network of China Southern Airlines and Jiangxi University of Science and Technology is not as convenient as that of Nanchang University.

In the spare time online, the persons who paid for it 0–4 hours are the largest, the persons who paid for it 4–6 hours are less, and the persons who paid for it 2–4 hours are the largest. In the 0–2 hours of Internet time, China Southern Airlines and Nanchang University have an equal proportion of the number of people, and Jiangxi Faculty of Economics and Social Sciences has the least number of people. In the 2–4 hours of online time, Nanchang University has the largest number of people, followed by Jiangxi Faculty of Economics and Social Sciences, and China Southern Airlines has the least. In the online time of more than 4 hours, the proportion of students in the three schools is relatively small.

In these three schools, there was a significant positive correlation between the online learning environment and behavioral engagement, emotional engagement, and cognitive engagement. And the weak to moderate associations are found between emotional, associative, and functional behavior. There is a statistically significantly positive relationship attained between the organization and management of e-learning process and behavioral, emotional, and cognitive engagement. And the associations from weak to intense are affective exposure, civic investing, and actional exposure.

5. Computer-Aided Particle Swarm Optimization Algorithm

5.1. Particle Swarm Optimization Algorithm. In the global model GPSO, the entire population shares information, a particle's neighbors consist of all other particles in the population, and the particle population evolves towards the optimal particle of the population. The topology used by the basic particle swarm algorithm (PSO) is a global topology, and the update formulas of particle velocity and position are as follows:

$$\begin{aligned} v_{id}^{a+1} &= w v_{id}^{a} + c_1 r_1 \left(p_{id}^{a} - x_{id}^{a}\right) + c_2 r_2 \left(p_{gd}^{a} - x_{id}^{a}\right) \\ x_{id}^{a+1} &= x_{id}^{a} + v_{id}^{a+1}. \end{aligned} \quad (1)$$

Among them, $p_{g\,d}^{a}$ in formula (1) is the global optimal position of the entire particle swarm. The GPSO algorithm model adopts the fully interconnected structure to construct the neighborhood topology of the particle swarm.

In the local model LPSO, particles communicate with their nearest neighbors only. It tracks the optimal position of the individual itself and the optimal position of all neighbors in the topology structure for evolution, instead of tracking the global optimal position of the entire population for evolution. The particle velocity and particle position update formulas are as follows:

$$\begin{aligned} v_{id}^{b+1} &= wv_{id}^{b} + c_1 r_1 \left(p_{id}^{b} - x_{id}^{b}\right) + c_2 r_2 \left(p_{ld}^{b} - x_{id}^{b}\right), \\ x_{id}^{b+1} &= x_{id}^{b} + v_{id}^{b+1}. \end{aligned} \tag{2}$$

Among them, p_{ld}^{b} in formula (3) is the local optimal position of all neighbors in the particle topology. The neighborhood topology constructed by the LPSO algorithm model adopts the von Neumann structure.

In the classical PSO mechanism, particles aggregate in the form of orbitals. For the convenience of analysis, it is assumed that the particle moves in one-dimensional space, and the point p is the center point of the Delta potential field; then the potential energy of the particle in the one wavelength delta level shaft is

$$V(m) = -\gamma * \delta(m - p). \tag{3}$$

From formula (5), the wave function of the particle can be obtained as

$$\theta(m) = \frac{1}{\sqrt{L}} * \exp(-\|p - m\|/L). \tag{4}$$

In the formula, the parameter L depends on the width of the potential well and is used to determine the search range of the particle. The probability density and distribution function of the wave function can be obtained as

$$\begin{aligned} Q(m) &= |\theta(m)|^2 = \frac{1}{L} * \exp(-2\|p - m\|/L), \\ D(n) &= \int_{-\infty}^{n} Q(n)dn = \frac{1}{L} * e^{-2nL}. \end{aligned} \tag{5}$$

The positions of the particles can be obtained as

$$m(t+1) = p \pm \frac{L(t)}{2} * \mathrm{In}\left(\frac{1}{u}\right), \tag{6}$$

u is a random number uniformly distributed in (0,1), p is defined as a random number between the current optimal value pBest of the particle and the current optimal value gBest of the particle swarm, namely,

$$p = \frac{(pBest * \phi_1 + gBest * \phi_2)}{(\phi_1 + \phi_2)}, \tag{7}$$

where φ_1, φ_2 are a random number within (0,1); the value of $L(t)$ is defined as

$$L(t) = 2 * \alpha * |p - m(t)|. \tag{8}$$

In addition, the mean of the current optimal value of all particles in the particle swarm is defined as $m$best, namely,

$$mbest = \frac{1}{X}\sum_{i=1}^{M} P_{i1} = \left(\frac{1}{X}\sum_{i=1}^{M} P_{i1}, \frac{1}{X}\sum_{i=1}^{M} P_{i2}, \frac{1}{X}\sum_{i=1}^{M} P_{i3}, \ldots \frac{1}{X}\sum_{i=1}^{M} P_{id}\right). \tag{9}$$

M is the population size of the particle swarm, P_i is the optimal value of the i-th particle in the population, and formula (11) is redefined as

$$L(t) = 2 * \beta * |mbrst - m(t)|. \tag{10}$$

Substituting the above formula into formula (9), we get

$$m(t+1) = p \pm \alpha * |m\mathrm{best} - m(t)| * \mathrm{In}\left(\frac{1}{u}\right). \tag{11}$$

It is the formula of motion of particles in QPSO.

5.2. Computer Algorithms. The idea of the simulated annealing algorithm (SA) is derived from solid-state annealing. It heats the solid by increasing the thermal motion of the solid particles. As the temperature T increases, the particles deviate more and more from their equilibrium position. The energy E of the system increases until the temperature reaches the dissolution temperature. At this temperature, the solid loses its regularity completely and dissolves into a liquid. The energy of the system is also reduced as the temperature is slowly lowered. Gradually nonuniform motion of the particles occurs. Finally, it reaches an equilibrium state at room temperature and the internal energy is reduced to a minimum. This process is called annealing. During the annealing process, it is only when the temperature is slowly lowered that it finally reaches the energy minimum of the system. It ensures that the system reaches equilibrium at any temperature.

The expression for the simulated annealing algorithm is as follows:

$$P_{in}(T) = \{M_{k+1} = n | M_k = i\} = \begin{cases} g_{in}(T)a_{in}(T), & \forall n \in \Omega_i, \\ 0, & \forall n \notin \Omega_i. \end{cases} \tag{12}$$

Because $a_{in}(T)$ is not always equal to 1, the new solution may not be accepted, and the probability that the algorithm stays at solution i is

$$P_i(T) = 1 - \sum_{n \in \Omega} P_{in}(T). \tag{13}$$

Since Ω is a listable set, the random process expressed by the random variable generated by SA is a Mapkob chain; that is, the further transition probability is

$$P(T) = \begin{bmatrix} P_{11}(T) & P_{12}(T) & \cdots & P_{1|\Omega|}(T) \\ P_{21}(T) & P_{22}(T) & \cdots & P_{2|\Omega|}(T) \\ \vdots & \vdots & \ddots & \vdots \\ P_{|\Omega|1}(T) & P_{|\Omega|2}(T) & \cdots & P_{|\Omega||\Omega|}(T) \end{bmatrix}. \tag{14}$$

Then the transition probability of step k is

$$P(x, x+k) = \begin{cases} \prod_{t=x}^{x+k-1} P(T_t), & k \geq 1, \\ I, & k = 0, \end{cases} \tag{15}$$

I is the identity matrix, and T_t represents the temperature value of the t-th iteration.

Several parameters in the simulated annealing algorithm that control the operation of the algorithm are called the cooling scheme. The cooling scheme ensures that the simulated annealing algorithm completes in a limited time.

6. Conclusion

With the rapid development of network and multimedia technology, online learning platforms are more and more widely used in the field of education, and they are becoming more and more popular. The development of e-learning and the use of e-learning platforms offer the possibility of lifelong learning as they facilitate the acquisition of learning and thus are a new way of learning for most e-learners. Online learning platforms not only allow learners to study anytime, anywhere, but also provide situational teaching that traditional classroom learning cannot match. And they realize personalized learning. Learners can switch from passive learning to autonomous learning. The emergence of online learning platforms is a shock to the education sector. And it has led to a huge change in the way of education. The research on multimedia computer-aided teaching platform based on particle swarm optimization algorithm is also of great significance for promoting the current scientific development.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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