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PAPER

Construction of an Online Learning Resource Recommendation Model Based on Artificial Raindrop Algorithm in the Context of Smart Education

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ABSTRACT

The explosive growth of online education has transformed traditional teaching, resulting in difficulties such as course selection, complex learning paths, and information overload. This study proposes an online resource recommendation (RR) model based on the artificial raindrop algorithm (ARA) to address these issues. In smart education (SE), the study first establishes a learner model (LM) to capture learners' personalized needs and characteristics. The ARA is then used to construct an online learning RR model, simulating raindrops' search to find the optimal learning resources. A perturbation mechanism is introduced to improve the algorithm's diversity and search ability, enhancing the quality of recommendations. Experiments showed the proposed algorithm's training time of 3.605 seconds, shorter than comparison algorithms, and better accuracy, recall, and F1 scores of 0.9531, 0.07639, and 0.1272, respectively. This study offers new methods and ideas for improving course selection and learning paths in online education platforms.

KEYWORDS

smart education (SE), artificial raindrop algorithm (ARA), online learning resources recommendation (OLRR), learner model (LM), disturbance mechanism

1 INTRODUCTION

The explosive growth of online education has changed traditional teaching methods, enabling learners to learn anytime, anywhere. However, the accompanying era of big data has brought many problems to online education platforms. Firstly, it is difficult for learners to find courses that are suitable for themselves among the numerous courses [1]. Secondly, the learning path of learners is often complex, while the training programs of schools tend to be single and repetitive, resulting in low learner satisfaction and poor teaching effectiveness [2, 3]. In addition, most online education platforms lack effective learning guidance and

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course planning, and learners lack a deep understanding of the overall knowledge structure. And the learning resources on the Internet are very large, which makes learners fall into a large number of course choices and leads to information overload and low pass rates [4]. Traditional education models also find it difficult to timely discover the learning goals of learners. Therefore, it is urgent to propose appropriate learning resources recommendation (RR) methods to address the aforementioned issues [5]. And the development of intelligent algorithms is in full swing, bringing new opportunities for the recommendation of online learning resources [6]. The artificial raindrop algorithm (ARA) originates from the phenomenon of natural rainfall. By analyzing the rainfall process, its entire optimization cycle is summarized into six stages, thus achieving an efficient optimization algorithm with good applicability for recommending learning resources [7, 8]. Therefore, in order to better achieve the effectiveness of online learning resources recommendation (OLRR) and support the development of smart education (SE), this study proposes an OLRR model based on ARA. The innovation of this study is firstly the construction of the learner model (LM) in SE. Secondly, by integrating ARA and LM, OLRR is constructed. Finally, in response to the weak local and global search capabilities of ARA, a perturbation mechanism is introduced to perturb individuals to increase the diversity and search capabilities of the artificial raindrop algorithm.

The rest of the text is organized as follows: The second part provides an overview of the technologies used. The third part is the construction of the technology used in the study. The fourth part analyzes the performance of the proposed technology. The fifth part summarizes the entire text and provides an outlook.

2 RELATED WORKS

Resource recommendation models play an important role in various industries, and a large number of scholars have conducted relevant research on RR models and technologies. Some scholars conducted research on user interests in Internet of Things (IoT) services and constructed a new recommendation model based on time-varying relationships [9]. It considered the correlation between user interests and time, clustering users with similarity to achieve faster and more accurate recommendations. It could also analyze user behavior to achieve better recommendation results. These results confirmed that the proposed algorithm was feasible in IoT. Some scholars proposed an intelligent recommendation algorithm based on machine learning, which could be used in the medical field to automate clinical guidance for patients and perform pre-diagnosis [10]. This algorithm improved the learning process through clustering, making it more accurate and representative in the diagnosis. By collecting actual data and conducting empirical research on the proposed theory and method, the application value of this method in online health management was verified. Some scholars organically combined intelligent models and knowledge recommendation techniques to develop an online English education system [11]. This method combined the decision tree algorithm with a neural network for English teaching RR. It could extract valuable information from massive amounts of data, summarize patterns and data, and assist teachers in improving teaching quality and student English performance. These results confirmed that this system could effectively improve the learning efficiency of students and enhance the targeted learning. Some scholars proposed a group recommendation method based on multiple attention mechanisms, mainly used to understand the group's preferences for topics and predict the next topic that the group is interested in [12]. This method fully utilized the deep network structure of multiple attention items to achieve accurate group recommendations. This model utilized multiple attention networks to learn the intrinsic social attributes of groups by vector representation of group features and group preference learning. Numerous experiments had been conducted on two actual datasets, confirming that this method could effectively solve group recommendation problems. Some scholars introduced neural networks into service recommendation and established a new service recommendation system [13]. A new method combining fuzzy clustering with reconstruction of embedded network denoising autoencoder was proposed to address model overfitting. This method could effectively solve the algorithm performance being easily affected by the clusters. Through testing various data densities, both network structures could effectively improve system performance and reduce overfitting issues.

The artificial raindrop algorithm is a relatively novel search algorithm, and many scholars have conducted research on it. ARA is inspired by the phenomenon of rainfall in nature. By simulating the process of raindrops flowing, colliding, and gathering from high to low under the action of gravity, ARA seeks the optimal solution to the problem. This algorithm has high efficiency and adaptability and can demonstrate strong solving ability in various complex optimization problems. There are scholars who proposed a hybrid metaheuristic method that combined the long short-term memory (LSTM) classification model with the ARA-harmony search algorithm (ARA-HSA) [14]. It could implement high-performance intrusion detection systems in cloud computing. This method conducted in-depth research on existing intrusion detection data, providing strong technical support for the classification and prediction of intrusion detection systems. Finally, experiments were conducted on the hybrid algorithm using a standard IDS database, and a comparative analysis was conducted with other latest hybrid algorithms. Some scholars started from the acoustic noise reduction of switched reluctance motors and used ARA to achieve SRM torque control, minimizing torque fluctuations [15]. The proposed method analyzed the impact of torque ripple control on noise control and optimized the torque ripple control method of SRM. This study intended to use MATLAB to simulate the proposed control strategy and compare it with a direct torque control PI controller based on fuzzy gain allocation for verification. Some scholars conducted research on ARA, using multiple multidimensional testing functions and benchmark functions to introduce and compare the results [16]. The research results indicated that the movement pattern of ARA was consistent with the behavior of natural raindrops. These results also confirmed the effectiveness of ARA in minimizing optimization functions and demonstrated the advantages of parallel computing restart technology in improving solution quality. This study was crucial for understanding and applying the potential of ARA in optimization problems and provided valuable references for further research and application. Some scholars combined ARA with time-delay control methods to establish a new parameter identification model for time-delay chaotic systems and performed parameter identification on it [13]. This model extracted correlated features from a series of system states through the application of a temporal attention mechanism, achieving time delay recognition. Then, a recurrent neural network was used to implicitly approximate the differential equations of the system, obtaining the algebraic equations of the system parameters. The simulation results verified the effectiveness of the proposed method. Some scholars developed a face recognition method that combined ARA and support vector machine (SVM) [16]. They applied the ARA optimization method to the parameter optimization of SVM, making it have better recognition accuracy. The experiment confirmed that the recognition accuracy of this method on the YALE database reached 86%, which was 81% compared to the benchmark paper. For parameter optimization, compared with the basic research results based on PSO-SVM, this algorithm could improve optimization performance by 5%.

In summary, although existing research has made some progress in the fields of RR and ARA, there are still some problems. For example, many recommendation algorithms used in research perform well in some optimization problems but are prone to falling into local optima and lack global search capabilities. Especially when dealing with complex multi-objective optimization problems, they show significant shortcomings. Moreover, existing recommendation systems often focus on a single feature of resource matching and fail to fully consider the multidimensional characteristics of learners, such as learning style, cognitive level, and learning goals, resulting in recommendation results that cannot accurately meet the personalized needs of learners. By simulating the random collision and flow of raindrops, ARA can avoid falling into local optima during the optimization process and has better global search capabilities and diversity. On this basis, the present study attempts to integrate ARA with LMs and design a new RR model to address the algorithmic limitations, lack of personalization, and weak dynamic adaptability of current technologies.

3 ONLINE LEARNING RESOURCE RECOMMENDATION MODEL BASED ON LM AND ARA

This section first constructs LM in the context of SE and targets the feature data of learners. On this basis, a mapping relationship between learners and resources is established through the feature data of learners and resources. Afterwards, an improved discrete ARA is introduced for learning resource recommendation.

3.1 Construction of learner model in the context of smart education

Smart education has become a hot topic in current education, receiving active promotion from various aspects such as policy support, social development, network economy, and technological support. The core of SE is to achieve personalized intelligent learning based on the needs of learners, supported by intelligent platform environments and intelligent teaching strategies [17]. However, in the context of education big data, although online teaching resources are becoming increasingly abundant, there is also resource information overload and uneven quality. In such a learning environment, learners are prone to encountering "resource information overload" and "knowledge loss," resulting in traditional resource push being unable to meet personalized needs [18]. Therefore, it is particularly important to intelligently customize teaching resources and learning strategies for learners. Figure 1 shows the research questions of smart education.

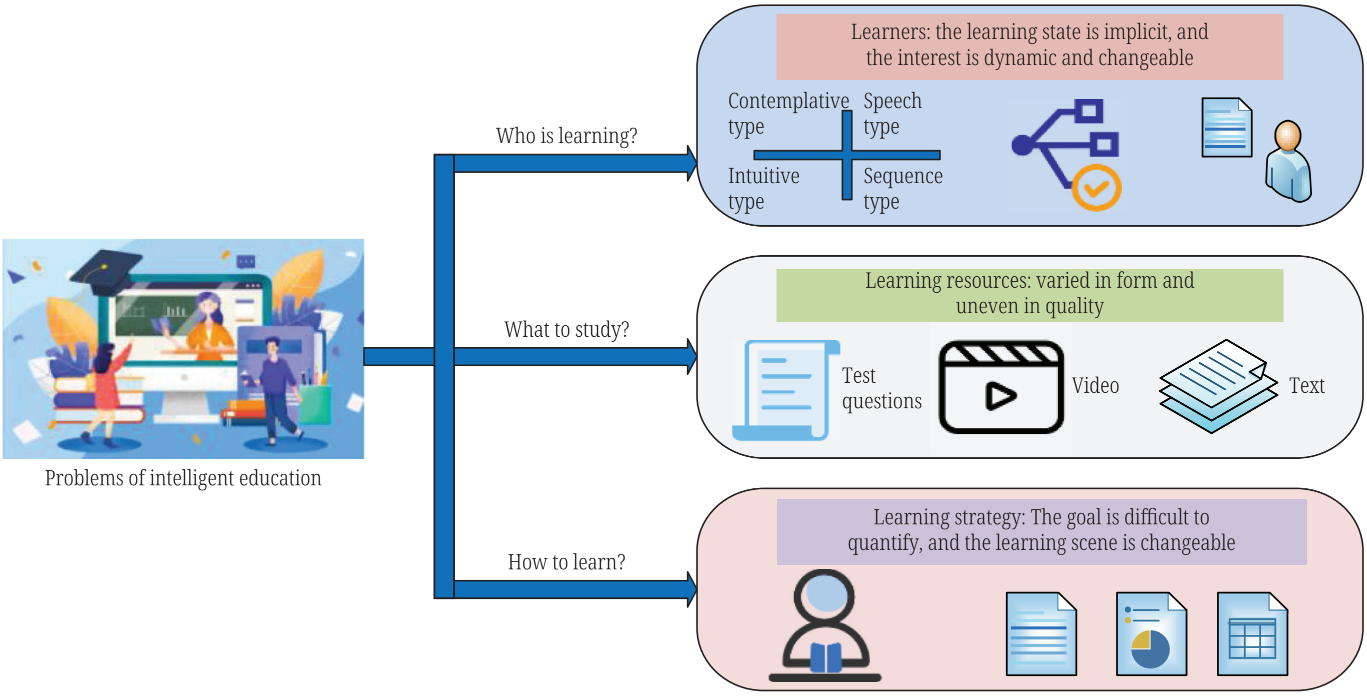

Fig. 1. Research problems of intelligent education

The way learners obtain learning materials through knowledge platforms has a significant impact on learning outcomes and processes. Under traditional methods, the system continuously allocates resources until it meets the needs of learners, but it consumes a large amount of resources. Online learning platforms enhance learner motivation through personalized RR, but it is necessary to consider the learner's cognitive status. The specific objectives of the research include dynamically capturing learners' personalized characteristics (such as cognitive level, learning style, learning motivation, etc.) and conducting in-depth analysis of them. Optimize the learning RR mechanism, reduce information overload issues, and enhance the personalization and effectiveness of learning resources. Design and implement dynamic adaptive learning strategies to provide flexible and efficient learning paths in different learning contexts. This study is based on learner and resource characteristics to optimize personalized RR and improve learning efficiency [19]. Through intelligent analysis and feedback, continuously optimize RR to enable learners to better access the required resources, increase learning time, and improve learning effectiveness. LM is a prerequisite for building a learning recommendation system, reflecting personalized parameters that reflect the dynamic changes of learners. LM includes information such as learning style, motivation, behavioral preferences, and learning objectives. In addition to representing the basic attributes of learners, the model also needs to express the knowledge mastery status of learners [20]. Currently, scenario-based LM is the most widely used, with most studies considering learner characteristics from multiple dimensions. And based on the learning scenarios under different tasks, an LM with scene characteristics is constructed using algorithm optimization parameters.

This study extracts personalized characteristics of learners, achieving matching goals between learners and resources and intelligent learning [21]. And it comprehensively considers factors such as learning goals, learning styles, and cognitive levels, dynamically adjusted and updated learning resources. The essence of implementing personalized learning resources is to accurately locate and match learners with resources. This study constructs a complete personalized learning RR based on the feature data of learners and resources [22].

According to the learning process of RR, the main attribute information involved in this study includes learner attributes and learning resource attributes. In addition to basic static information such as names and passwords, learner attributes also include dynamic information features such as learning objectives, emotional states, learning preferences, and learning styles. Dynamic features are important indicators for distinguishing personality differences among learners [23]. By utilizing the basic information of learners, they can be roughly divided first. The learning styles in dynamic features include perceptual and intuitive styles, while cognitive levels include recognition, understanding, and mastery. The mathematical expression of the learner is represented by Equation 1.

$$L = \{l_1, l_2, \ldots, l_U\} \tag{1}$$

In Equation 1, U represents the overall number of learners. l_U refers to the uth learner, and $1 \le u \le U$. The target knowledge points that learners expect to learn are represented by Equation 2.

$$K = \{k_1, k_2, \ldots, k_K\} \tag{2}$$

In Equation 2, K represents the number of target knowledge points. k_K refers to the kth knowledge point to be learned by the learner, and $1 \le k \le K$. Learning style is a personal characteristic exhibited by learners, which reflects their preferred learning behavior. The function of learning style is represented as $S = \{s_1, s_2, \ldots, s_q\}$. q represents the type of learning style. Learning style is an individual's gradually formed preference for learning methods, which describes the personalized characteristics of learners and the main reasons for the formation of different personal differences [24]. In recent years, learning styles have been mainly applied in learning path planning and recommendation, learning effect prediction and evaluation, and other aspects. This study mainly utilizes the activity sequences of learners with different preferences for learning content to recommend suitable learning resources to learners. The learning style prediction model is the most popular among the four learning style models. It is also recognized as the most comprehensive, detailed, and suitable learning style model for adaptive learning recommendation systems [25]. Figure 2 shows the calculation of learning style.

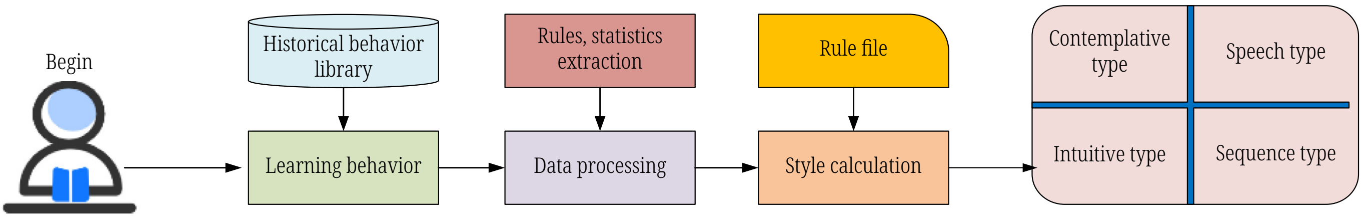

Fig. 2. The calculation process of learning style

The Felder-Silverman learning style scale is a commonly used tool for quantifying learner learning styles, where each dimension contains two relative types of learning styles [26]. Specifically, when the value of a certain type is high in a certain dimension, it indicates that learners tend to have a learning style of that type.

When the value of a certain type is low, it indicates a deviation from the learning style of that type. Based on this characteristic, the behavior patterns of learners can be divided into different dimensions. "+" indicates a bias towards this style type, and "–" indicates a deviation from this style type. Figure 3 shows the specific composition of the Field learning style scale.

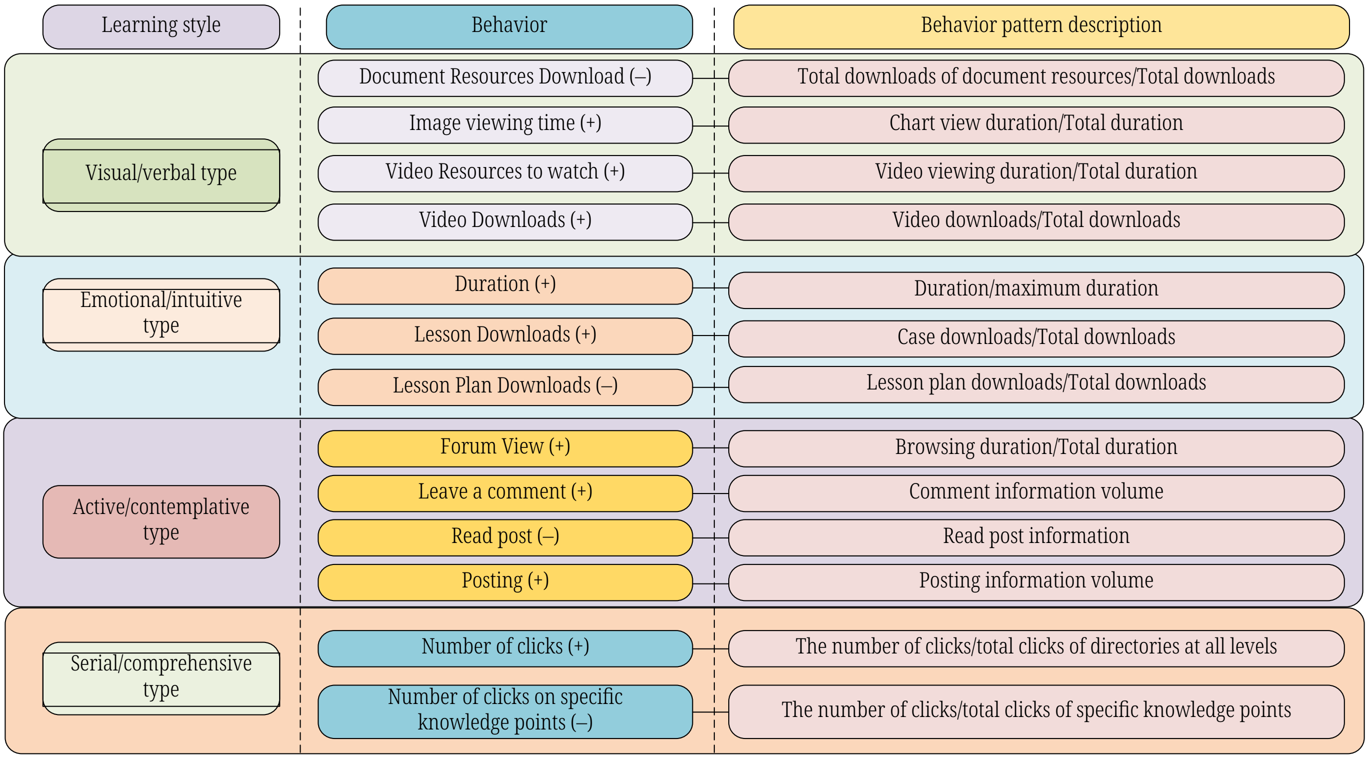

Fig. 3. The specific composition of the Field learning style scale

The modeling process of learning ability is called a cognitive diagnostic model, which can clearly and accurately obtain the cognitive status of learners towards knowledge points. The cognitive level of learners towards knowledge points is represented by Equation 3.

$$lc = \{lc_1, lc_2, \ldots, lc_U\} \tag{3}$$

In Equation 3, lc represents the cognitive level of U learners. The attributes of learning resources mainly describe the characteristic elements of resources, including information such as resource difficulty, media type, and relevance. Resource attributes include resource type, difficulty, etc. The types of resources include courseware, lesson plans, study plans, videos, and audio. Resource difficulty includes simple, moderate, difficult, etc. The learning resources are represented by Equation 4.

$$O = \{o_1, o_2, \ldots, o_N\} \tag{4}$$

In Equation 4, N represents the quantity of resources. o_N refers to the nth learning resource, and $1 \le n \le N$. The difficulty of learning resources is represented by Equation 5.

$$D = \{d_{k1}, d_{k2}, \ldots, d_{KN}\} \tag{5}$$

In Equation 5, d_{KN} represents the difficulty information of the nth resource corresponding to the kth knowledge point. The type of learning resources is represented by Equation 6.

$$E = \{e_1, e_2, \ldots, e_p\} \tag{6}$$

In Equation 6, e_p represents the type of learning resource. The correlation between learning resources and knowledge points is represented by Equation 7.

$$V = \{v_{k1}, v_{k2}, \ldots, v_{KN}\} \tag{7}$$

In Equation 7, v_{KN} represents the correlation between the nth resource and the kth knowledge point.

3.2 Construction of an online learning resource recommendation model that integrates ARA and learner models

To achieve personalized recommendations of learning resources, it is necessary to target the feature data of learners and consider the feature data of resources. In addition to considering the inherent static properties of resources, this study also analyzes learning behavior and considers factors such as learning costs. Therefore, this study investigates the optimization of personalized learning RR based on mapping relationships [27]. Specifically, the mapping relationship between learners and resources is first established through the feature data of learners and resources. Then, considering the learning cost of learners and the matching degree of resources, the optimal RR scheme is determined through optimization algorithms. Through this method, learners can be more accurately matched with learning resources that are suitable for their needs and interests, improving their learning outcomes and satisfaction with the learning process [28]. In addition, this study also evaluates and adjusts the recommendation results to continuously optimize the recommendation process and provide higher-quality personalized learning RR. The matching degree between the quantified learning style and resource type information features is represented by Equation 8.

$$f_{es} = \left(\sum_{q=1}^{Q} \sum_{p=1}^{P} \left| OS_{np} - le_{uq} \right| \right) / P \tag{8}$$

In Equation 8, q represents the type of learning style. Q represents the number of learning styles. OS A weighted sum representing the degree of matching between learning style and resource type. P refers to the level of mastery of knowledge points by students. le_{uq} means the learning style of learner u. The first layer of summation traverses all learning style types, while the second layer of summation further traverses all resource types based on each learning style. By quantitatively calculating the degree of matching between learners' learning styles and learning resource types, data support is provided for personalized recommendations to improve their targeting and accuracy. The learning behavior of learners can objectively reflect their value evaluation of the level of motivation towards positive goals. The analysis of learning costs can help accurately understand the learning preferences, needs, and behavioral patterns of learners, providing an important basis for personalized RR. By delving deeper into learning behavior data, it is possible to better understand the learning needs of learners, thereby providing more accurate and personalized learning RRs [29]. The learning cost of learners can be calculated using Equation 9.

$$f_c = \sum_{n=1}^{N}\left[\frac{1}{4}\left(\frac{\left|T-\sum_{i=1}^{n} t_i\right|}{T}+\frac{\left|R-\sum_{i=1}^{n} r_i\right|}{R}+\frac{\left|L-\sum_{i=1}^{n} l_i\right|}{L}+\frac{\left|H-\sum_{i=1}^{n} h_i\right|}{H}\right)\right] \tag{9}$$

In Equation 9, t_i represents the actual browsing time of a single resource. T refers to the total duration of resources. r_i means the actual number of views for a single resource. R is the suggested browsing frequency. l_i refers to the actual number of downloads of a single resource. L means the recommended number of downloads; the purpose is to optimize the utilization and performance of system resources by recommending an appropriate number of downloads. h_i is the actual collection amount of a single resource. H represents the recommended collection amount. Measure the cost of learners using resources, including factors such as browsing time, visits, downloads, and bookmarks. By calculating learning costs, we can better understand learners' preferences and behavioral patterns, providing reference for RRs. According to the learner's learning expectations, the correlation between resources and learning target knowledge points is represented by Equation 10.

$$\min F(x) = \omega_{dc} \cdot f_{dc} + \omega_{es} \cdot f_{es} + \omega_c \cdot f_c + \omega_r \cdot f_r \tag{10}$$

In Equation 10, f_{es} is the degree of matching between learning style and resource type characteristics. f_{dc} refers to the matching degree between recognition level and resource difficulty. f_c means learner costs. f_r represents the correlation between resources and learning objectives knowledge points. Currently, scholars are studying how to allocate weights to achieve optimal solutions for multi-objective optimization problems. In addition to multiple objective functions as the main components, multi-objective optimization problems also involve some equality and inequality constraints. Evolutionary computing is a subfield of intelligent computing, suitable for multi-objective optimization problems. Evolutionary algorithms are widely used in multi-objective problems by simulating the evolution of nature and guiding the population to approach the optimal solution. Personalized learning RR is a combinatorial optimization problem. There are issues with the existing recommendation strategy. This study comprehensively considers scale, constraint information, etc., and adopts an improved discrete ARA for learning RR, optimizing the recommendation results iteratively [30].

The artificial raindrop algorithm draws inspiration from natural rainfall phenomena. By analyzing the rainfall process, the entire algorithm optimization cycle is summarized into six stages: raindrop formation, descent, collision, flow, raindrop pool update, and water vapor update. ARA uses the altitude of raindrops to evaluate their condition and stores raindrops at lower altitudes in a raindrop pool. The key to algorithm optimization lies in the design of evolutionary operators. Figure 4 is a schematic diagram of the artificial raindrop algorithm.

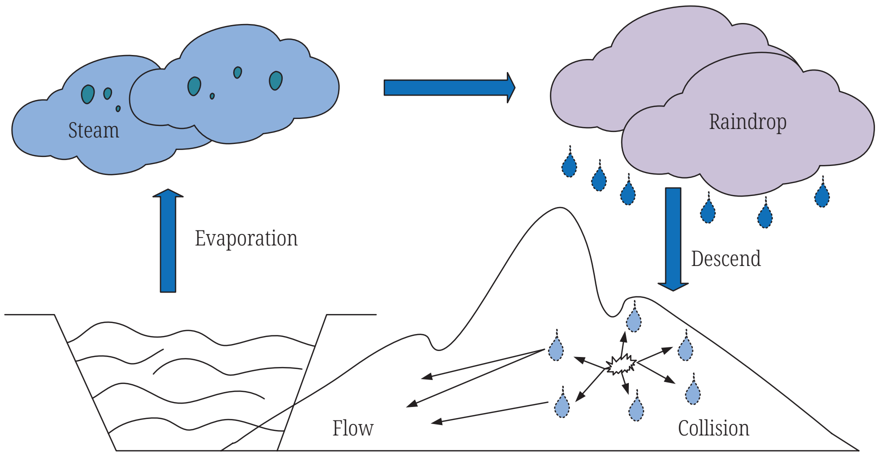

Fig. 4. Schematic diagram of ARA algorithm

Steam represents the initialization or generation of data. At the beginning stage of the algorithm, the system will generate an initial dataset or candidate solutions in some way. Evaporation represents the invalidation or elimination of information. As the algorithm progresses, certain information will gradually disappear, which can be seen as removing less effective solutions and improving the overall efficiency of the algorithm. Raindrop reflects the process of algorithm exploration in the search space, descend represents the optimization stage of the algorithm, and flow reflects the propagation and communication of information in the solution space. Collision represents the interaction between different solutions; for example, at certain points, multiple solutions may tend towards the same direction, prompting the algorithm to conduct deeper searches in these areas. Traditional ARA has certain limitations in certain situations, so this study proposes an improved algorithm, namely the differential ARA based on perturbation mechanism (ADARA). ADARA introduces a perturbation mechanism on the basis of traditional ARA, which increases the diversity and searchability of the algorithm by perturbing individuals. In ADARA, by introducing a differential mechanism, individual information is differentiated and transmitted to new individuals, thereby enhancing the algorithm's local and global search capabilities. Through this improvement, ADARA has higher efficiency and accuracy in solving combinatorial optimization problems, which can better cope with the challenges of solving complex problems. The purpose of encoding is to represent the feasible solution of the problem using a matrix. Common encoding methods include integer, floating-point, binary, and gray encoding. This study chooses integer encoding to initialize the raindrop population. Assuming the initial raindrop population is V_0, the number of populations is N, and V_i represents the ith generation population, then Equation 11 is the definition of the individual vector.

$$o_i^G = \left[o_{i1}^0, o_{i2}^0, o_{i3}^0, \ldots, o_{iD}^0\right] \tag{11}$$

In Equation 11, o_i^G represents the ith individual of the Gth generation population. This individual contains D structures. The values at each structure are integers, representing the resource number corresponding to the resource. All individual raindrops form the candidate solution set for the optimized problem. When raindrops fall and come into contact with the ground, they are knocked into several small raindrops. This study uses a probability selection strategy to select individuals with lower potential energy to participate in raindrop collisions. The concept of potential energy serves as a metaphorical representation of the quality or suitability of candidate solutions in optimization problems. In the structural fragments of individual raindrops, a pair of starting positions are randomly selected, and the structural fragments are exchanged to generate new raindrop individuals. Figure 5 shows the process of collision forming small raindrops.

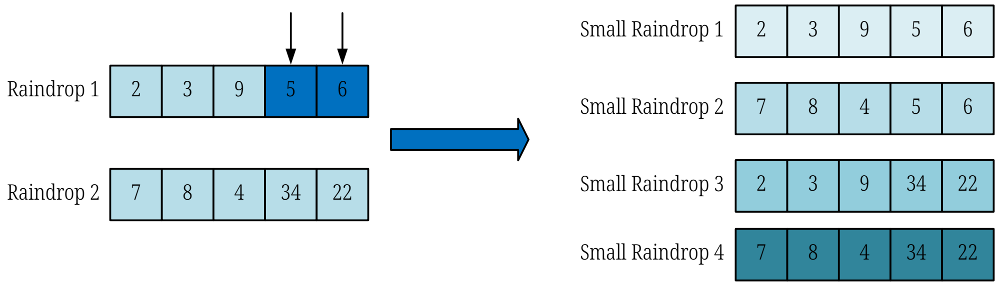

Fig. 5. Schematic diagram of raindrop collision process

Combining the RR problem, the potential energy referred to after raindrops fall is the objective function value of RR. $F(x)$ is the RR objective function. PE is the individual potential energy. The raindrop operator corresponding to the minimum PE is a high-quality solution for this model. The relationship between $F(x)$ and PE is represented by Equation 12.

$$PE = F(x) \tag{12}$$

In raindrop collisions, the higher the probability of collision, the easier it is for the structure of the old individual to be destroyed, and the faster the speed at which new individuals are generated. A high collision rate can damage excellent individuals, while a low collision rate can lead to algorithm stagnation. The calculation of collision rate is represented by Equation 13.

$$P_c = \begin{cases} \dfrac{1}{1+\exp\left(A\left(\dfrac{2\left(ColRain_r^G - ColRain_{avg}^G\right)}{ColRain_{best}^G - ColRain_{avg}^G}\right)\right)} & f \geq f_{avg} \\ rand(0.5,1) & f < f_{avg} \end{cases} \tag{13}$$

In Equation 13, A represents the optimal value of the basic activation function. $ColRain_r^G$ is the current solution after raindrop collision. $ColRain_{best}^G$ means the optimal solution after raindrop collision. $ColRain_{avg}^G$ refers to the average solution after raindrop collision. By adjusting the collision rate, the global exploration and local development capabilities of the algorithm can be balanced, and the convergence speed and accuracy of the algorithm can be improved. The calculation of the raindrop flow operator is represented by Equation 14.

$$Raindrop_i^G = \begin{cases} ColRain_{best}^G + rand_a\left(ColRain_{r1}^G - ColRain_{r2}^G\right) & rand > 0.5 \\ ColRain_{r0}^G + rand_b\left(ColRain_{r1}^G - ColRain_{r2}^G\right) & rand \leq 0.5 \end{cases} \tag{14}$$

In Equation 14, $ColRain_{r0}^G$, $ColRain_{r1}^G$, $ColRain_{r2}^G$, $rand$, $rand_a$, $rand_b$ are random numbers are uniformly distributed in the interval [0, 1]. After raindrops collide and flow, the entire population will evolve towards the current optimal solution. The current optimal solution may be a global optimal solution or a local optimal solution. If the current solution is the global optimal solution, raindrops can survive and will not be eliminated. If the current solution is a local optimum, the entire population will fall into a local optimum, and the generated new solution will be near the local optimum. To escape from the local optimal solution, this study introduces a perturbation strategy in the differential flow operator, represented by Equation 15.

$$Raindrop_i^G = ColRain_{\min}^G + rand\left(ColRain_{\max}^G - ColRain_{\min}^G\right) \tag{15}$$

In Equation 15, $ColRain_{\max}^G, ColRain_{\min}^G$ represent the upper and lower limits of the current solution after raindrop collision, respectively. Figure 6 shows the improved ARA in this study.

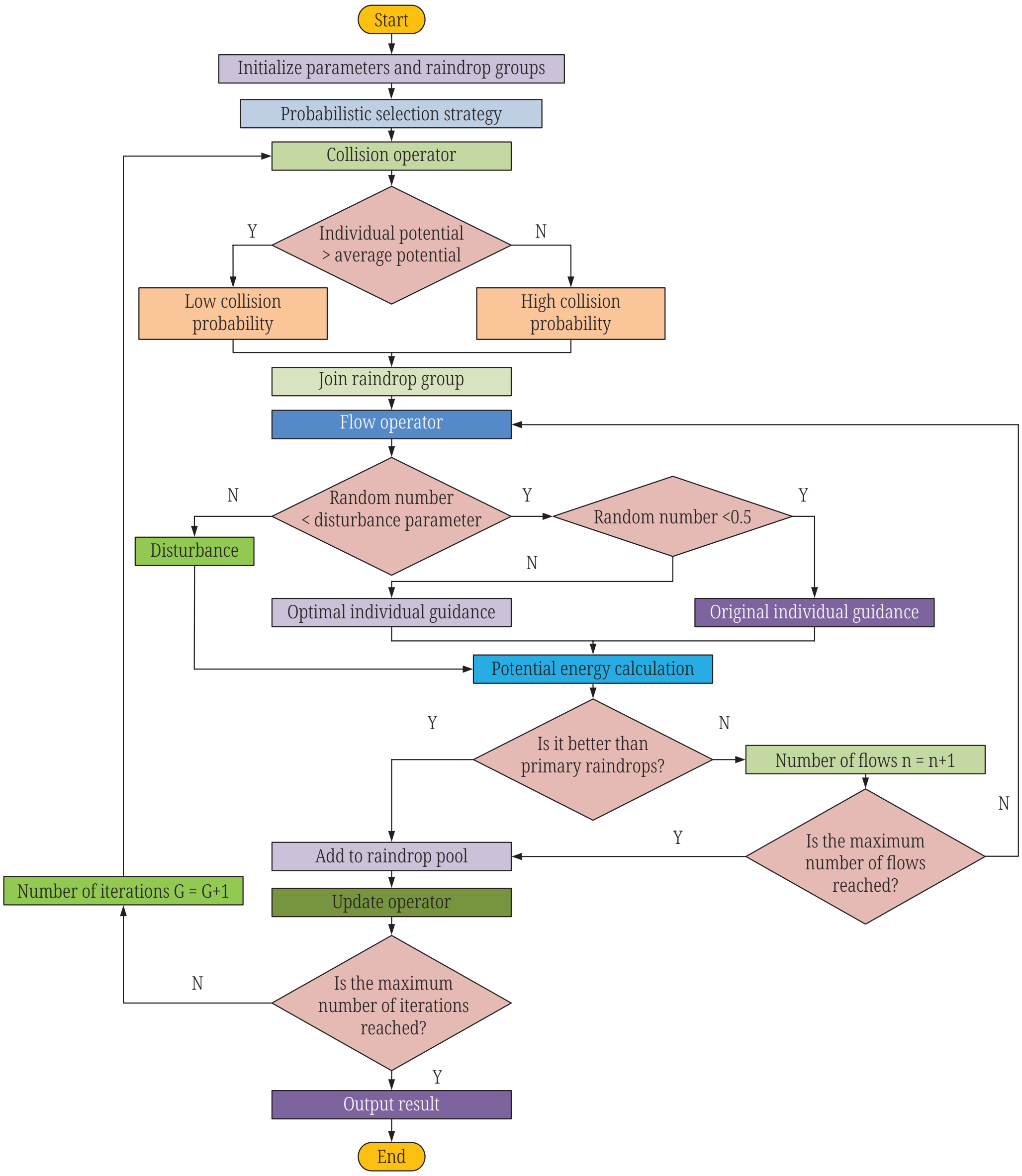

Fig. 6. Operation flow of the ADARA algorithm

As shown in Figure 6, the ADARA algorithm steps include initializing parameters and random groups, performing probability selection and collision operations, evaluating low collision probabilities, generating random perturbations, and calculating potential energy to determine the optimal individual guidance. The algorithm continuously iterates and updates by adding the calculated individuals to a random group and checking if the maximum number of iterations has been reached. Finally, the algorithm ends when the preset conditions are met, completing the RR. The entire matching and recommendation process is to obtain dynamic information such as the learner's learning style through the LM. Calculate the potential value of each learning resource based on factors such as matching degree and learning cost. Optimize the potential value through the ADARA algorithm and iteratively select the resource set with the lowest potential value as the recommendation result. Output an optimized list of recommended learning resources, sorted by potential value.

4 PERFORMANCE VERIFICATION OF ONLINE LEARNING RESOURCE RECOMMENDATION MODEL BASED ON LEARNER MODEL AND ADARA

This section first evaluates the operational performance of the proposed model through validation. In the validation, indicators such as running time and resource consumption of the model were measured and analyzed. Next, this section provides a detailed analysis of the actual application effects of the model. By evaluating the performance of the model in different scenarios, the advantages and disadvantages of the model in terms of accuracy, stability, and reliability in practical applications can be identified. These analysis results provide valuable guidance and reference for further improving and optimizing the model.

4.1 Performance analysis of learning resource recommendation model based on ADARA

To verify the performance of ADARA in handling RR problems, this study conducted experiments using ADARA, difference algorithm (DE), and discrete particle swarm algorithm (DPSO). The simulation experiment environment is the Windows 10 operating system, the programming tool is PyCharm 2019.1.1, the hardware environment is the Intel processor i5-6250, and the running memory is 8GB.

The cognition of learners on five knowledge points was selected as the research object, and five knowledge points of middle school mathematics were selected as the learning objectives. The learner's cognition, preferred learning methods, etc., are known, and the difficulty level of resources is also known. Learners were classified based on their learning goals, learning styles, and cognitive levels, and learners A to D were randomly selected for the experiment and analysis. Classification refers to dividing learners into several categories with similar attributes based on their personalized characteristics, in order to more effectively recommend learning resources. These four learners have different characteristics including their mastery of knowledge points, preferred learning methods, different learning objectives, and different behavioral records generated on the learning platform. The experiment selected five knowledge points from the "Rational Numbers" section of junior high school mathematics as experimental data, each knowledge point containing 10 resources of different difficulty levels, with a total of 50 learning resources. The problem parameter model provides a range of parameters for learner learning style, cognitive level, and resource difficulty. Although only four learners were used, the data diversity of the four selected subjects ensured the generalizability of the experimental results, and sufficient learning resources were utilized, with each subject having a different recommendation sequence. The diversity of resources can supplement the insufficient number of subjects, thereby fully testing the performance of the recommendation system. Table 1 shows the specific experimental parameters.

Table 1. Experimental parameters

Parameter	Experiment 1	Experiment 2	Experiment 3	Experiment 4
Learner	A	B	C	D
leu	8 learning styles			
lcu	Knowledge level, value range [0, 1]			
D	The k-th knowledge point corresponds to the difficulty of the n-th resource, and the value range is [0, 1]			
E	Five resource types			
V	The degree of correlation between the n-th resource and the k-th knowledge point, the value range [0, 1]			

To gain a more intuitive understanding of the changes in solution accuracy during the algorithm iteration process, this study conducted 200 algorithm executions on four cases and recorded the variation curves of the mean in Figure 7. By observing these curves, the convergence of the algorithm and the changes in solution accuracy are better understood in the iteration. By analyzing the curve, the mean gradually converged or fluctuated as the iterations increased. These curves provide intuitive information to help evaluate the performance and effectiveness of algorithms in experiments.

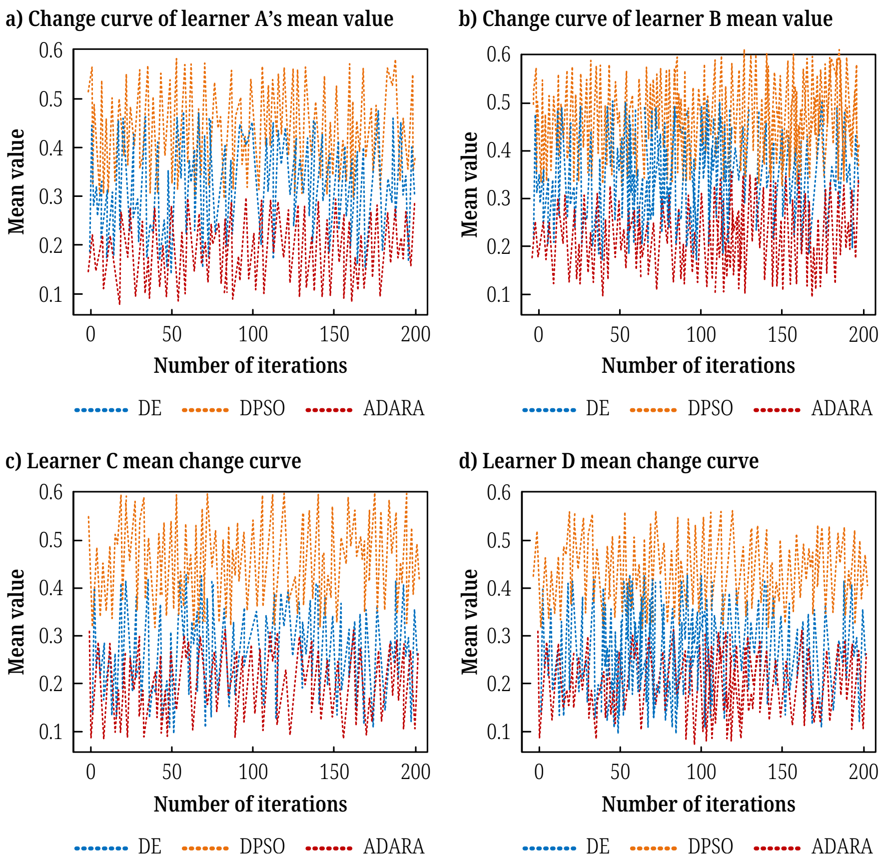

Fig. 7. Change curve of the mean value of the four groups of experiments

Figure 8 shows a comparison of the function iteration curves of three algorithms under four sets of experiments. If there is a gradual decrease in the optimal value, it indicates that the algorithm is iteratively optimizing and constantly finding resource combinations that better meet the needs of learners. If the optimal value fluctuates, it may reflect the algorithm's balance adjustment between global search and local development. When the optimal value tends to stabilize, it indicates that the algorithm has approached the global optimal solution; that is, the quality of the recommendation results has reached the optimal level. The optimal value for each iteration was taken, and the iteration curves of three algorithms were drawn. The graphs were easy to visually analyze and compare the optimization process of each algorithm's RR. Compared with DE and DPSO, ADARA could maintain good convergence characteristics while meeting the personalized needs of learners, indicating that ADARA-optimized online learning resources were more suitable for learners. These four test cases were randomly selected from the experimental dataset, representing learners with different personality traits. Therefore, ADARA had good universality in dealing with learning RR problems.

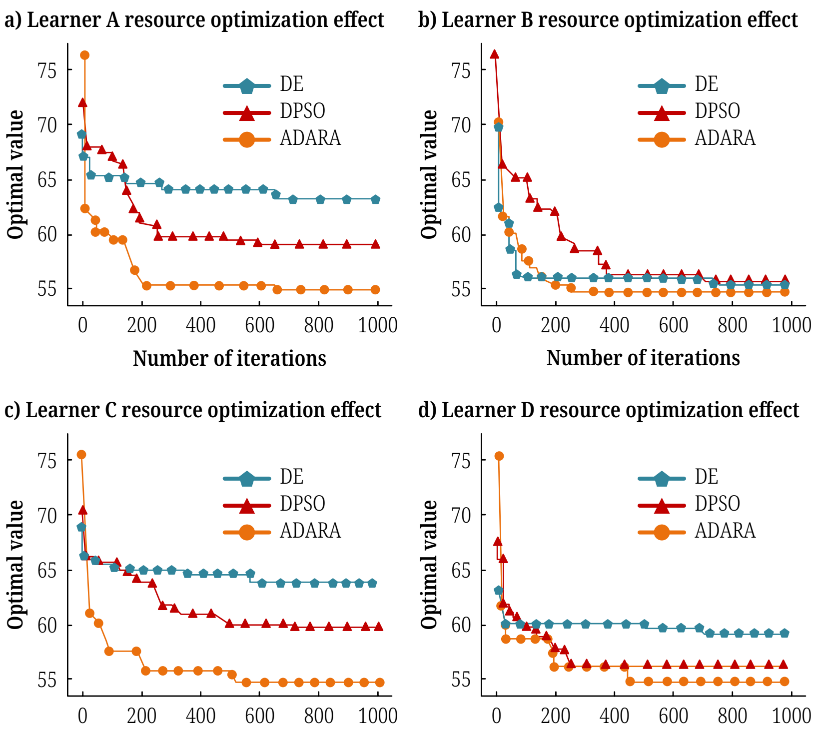

Fig. 8. Comparison of function iteration curves of the three algorithms under four groups of experiments

To more intuitively see the distribution of solution sets, Figure 9 shows the box plots of solution sets for three algorithms in four sets of experiments. The data obtained by ADARA were generally closer to the horizontal axis than the data obtained by other algorithms, indicating that the solution obtained by ADARA was superior to the comparison algorithms. In experiments A and B, ADARA obtained the smallest data range, indicating that ADARA had better stability. In experiments C and D, the data obtained by ADARA were also closer to the horizontal axis and had the smallest range of data, indicating that ADARA not only had good convergence performance but also had good stability. Therefore, the proposed ADARA had good convergence performance.

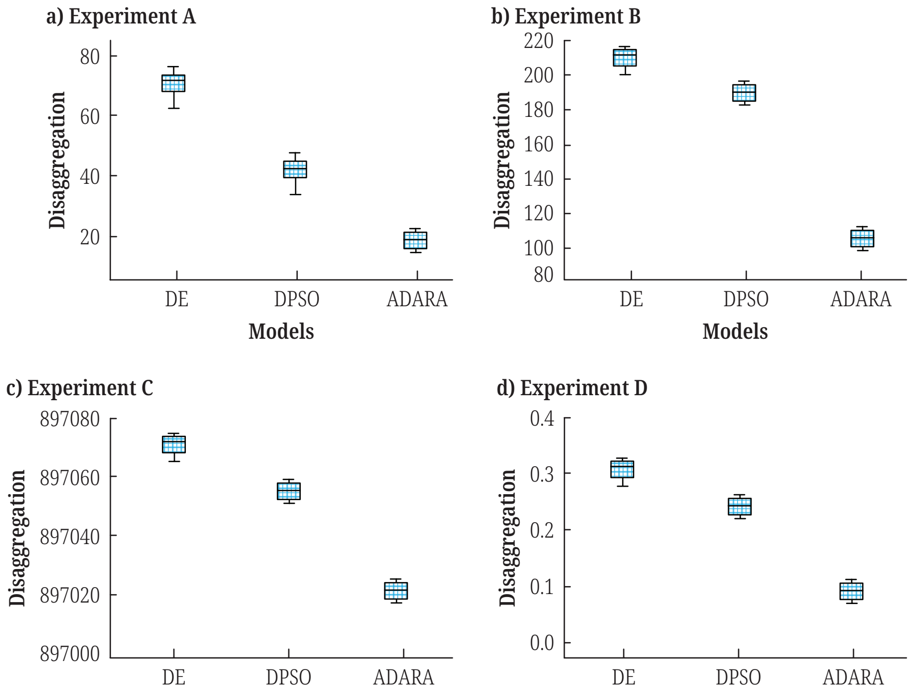

Fig. 9. Solution box whiskers of four algorithms on four groups of experiments

Figure 10a shows the mean variation curve of the optimal solution. Figure 10b shows the success rate curve of the algorithm converging to the global optimum. By observing these two curves, as learning resources and learners increased, ADARA performed significantly better than other algorithms in terms of solving accuracy and success rate. This meant that ADARA could more accurately recommend learning resource sequences and had higher reliability. In contrast, other methods performed poorly in terms of solving accuracy and success rate. Therefore, ADARA had better performance in personalized learning RR and could provide learners with more accurate and reliable learning resource sequences. This conclusion helped to further understand and apply ADARA and provide better solutions for personalized learning resources recommendations.

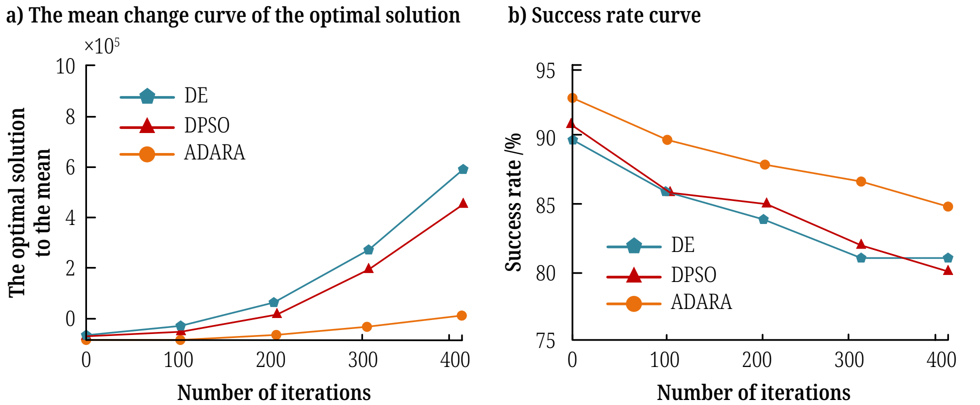

Fig. 10. Change curves of the mean value and success rate of the optimal solutions of the three algorithms

Figure 11 shows the average convergence time of each algorithm to the global optimal execution time for each group of experiments. With the increase of learning resources and learners, the complexity and scale of the problem had increased, and the execution time of all three algorithms had significantly increased. In the same set of experiments, ADARA's execution time was slightly lower than other algorithms. The reason is that ADARA can quickly converge to the optimal value when other algorithms are trapped in local optima and difficult to converge. Additionally, ADARA had a high success rate and an average execution time that was shorter than other algorithms. Therefore, in terms of time performance, ADARA was also superior to other methods.

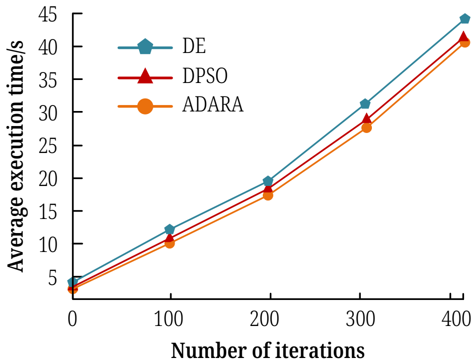

Fig. 11. The mean value of each algorithm converges to the global optimal execution time

In Figure 12, using DPSO and ADARA for RR calculation, two different Pareto front surfaces were obtained. The X-axis refers to the difference between learning resource types and user learning preferences. The Y-axis refers to the distance between the knowledge points contained in the learning resource and the user's knowledge base. The Pareto front mask obtained by ADARA had good distribution characteristics and good diversity, which had better convergence performance. This indicated that ADARA had superior search performance on the Pareto front and was more suitable for solving multi-objective learning RR problems. This conclusion helped to better understand and compare the performance of different algorithms on multi-objective problems and further optimize the effectiveness of learning resource recommendations.

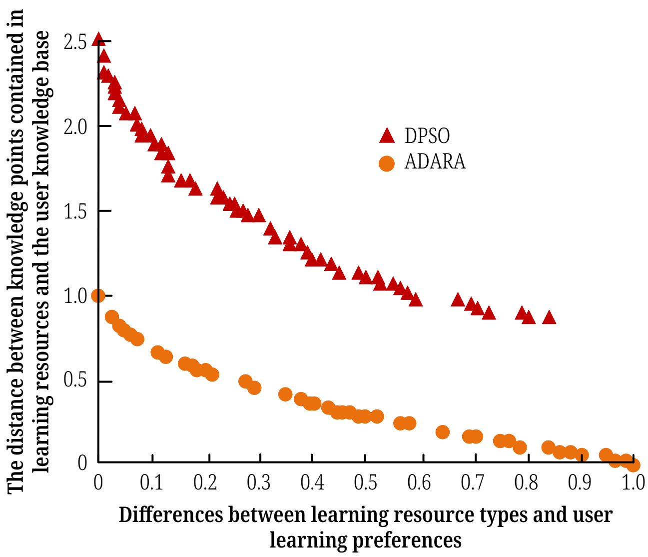

Fig. 12. Pareto front of discrete particle swarm algorithm and ADARA

4.2 Practical application analysis

This study selected some knowledge points from Java courses. In order to verify the differential advantages of the recommended learning resource sequence in this paper, considering the personalized needs or unique features of learner D, the actual application effect may deviate. Therefore, learning resources are recommended to learners A, B, and C. The initialization parameters for three learners were different, and 20 learning resources were numbered from 1 to 20, so each learner could obtain an RR sequence in Figure 13. The resource sequences recommended by ADARA showed significant differences, while the sequences recommended by DPSO were relatively similar. This indicated that ADARA had a strong adaptability to the problem, had a better ability to mine resources that meet the needs of learners, and could recommend resources with higher matching degrees for learners with different features.

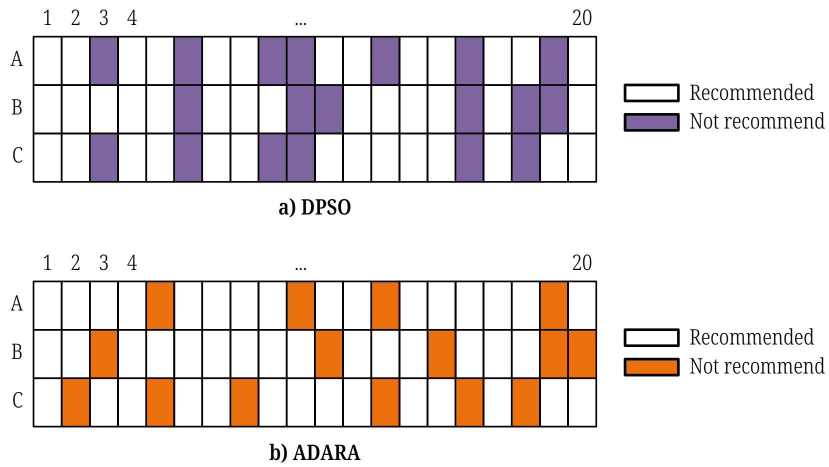

Fig. 13. Schematic diagram of learning resource recommendation sequence

This study compared the performance of different algorithms. Table 2 shows the comparison between the ADARA recommendation algorithm and DPSO in terms of cost and experimental performance, including the comparison of training and prediction time. These results indicated that in terms of training time, ADARA was 3.605 seconds, which had a shorter training time compared to DPSO. In addition, ADARA outperformed DPSO in precision, recall, and F1 of 0.9531, 0.07639, and 0.1272, respectively. The reason for the low recall and F1 values in the research method is that the total amount of learning resources and knowledge points used in the experiment is relatively large, but each learner may only focus on a few target knowledge points. This situation can lead to a lower number of matches between recommended learning resources and learners' target knowledge points, resulting in a lower recall rate. The F1 score is the weighted average of precision and recall. Due to the low recall rate, the F1 score will also be affected. This meant that ADARA could train faster in RR tasks and provide more accurate recommendation results. This result was crucial for selecting the appropriate algorithm to improve the effectiveness of RR. Through these comparative results, the performance of different algorithms in RR tasks was better understood and evaluated, and better solutions were provided for personalized learning.

Table 2. Comparison results of ADARA and DPSO in terms of cost and experimental performance

Comparison Item	DPSO	ADARA
Training (epoch)/s	1.542	1.115
Total training time/s	5.267	3.605
Predicted total duration/s	0.141	0.127
Precision	0.8541	0.9531
Recall	0.07591	0.07639
F1	0.1264	0.1272

5 CONCLUSION

To better achieve the effect of OLRR and support the development of SE, this study proposed an ADARA-based OLRR. The study selected DE and DPSO for comparative validation. These experiments confirmed that the mean values of these three algorithms gradually converged or fluctuated with increasing iteration times. Compared with DE and DPSO, ADARA could maintain good convergence characteristics while meeting the personalized needs of learners. The solution box plots of these three algorithms confirmed that the data range obtained by ADARA was smaller than other algorithms, which had better stability. In the curves of the mean and success rate of the optimal solution, with the increase of learning resources and learners, ADARA performed significantly better than other algorithms in terms of solving accuracy and success rate. It had better performance in personalized learning RR. ADARA had a high success rate, and its average execution time was also less than other algorithms. In addition, the Pareto front mask obtained by ADARA had good distribution characteristics and good diversity, which had better convergence performance. The actual application results have confirmed that the resource sequences recommended by ADARA have significant differences, while the sequences recommended by DPSO are relatively similar. This indicates that ADARA has a strong adaptability to the problem and has a better ability to explore resources that meet the needs of learners. The limitation of this study is that there is limited exploration of other factors related to personalized learning, and improvements can be made in the future.

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