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An Adaptive Learning Path Intelligence Recommendation Model for Vocational Competency Education

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Abstract. *In vocational competency education, adaptive learning (AL) can develop learning paths and recommend learning resources in a timely manner to meet students' individual needs. However, existing research cannot accurately recommend learning paths for learners that meet their characteristic needs. To this end, this paper firstly designs an OSKG architecture for vocational competence education, accomplishes entity extraction and entity alignment, and establishes inter-entity relationships by combining rule-based relationship extraction techniques. On this basis, the learner model is constructed from the dimensions of basic attributes, learning styles, and cognitive levels, and the mathematical model of AL path planning is established, and the constructed objective function is used as the fitness value of the AL path, and the optimized particle swarm algorithm (PSO) is adopted to address the target function. Mark the set of mastered knowledge points in OSKG as the starting point of the path, take the target knowledge point as the end point of the path, add the knowledge points with connected paths between the starting point and the end point set into the solution space, and search for the optimal path in the solution space. Eventually, the associated resources are sorted and filtered to obtain a collection of recommended sequences of learning resources. The experimental results imply that the offered model can provide learners with a learning path with high matching degree and effectively improve the recommendation accuracy.*
Keywords: Vocational competency education; Knowledge graph; Adaptive learning; Particle swarm algorithm; Learning path recommendation

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1. **Introduction.** In the wave of the digital era, vocational competency education and lifelong learning models are witnessing unprecedented changes. Traditional learning models are being replaced by smart online learning environments that are personalized, flexible and seamlessly accessible [1]. Intelligent online education platforms can provide users with

massive amounts of learning materials, which can lead to learner disorientation [2] and cognitive overload [3]. It is extremely important for learners to be provided with personalized learning paths and real-time tracking of learners' status changes, so that they can find their own way of learning among the vast amount of learning resources and keep abreast of their own learning situation. Adaptive Learning (AL) path planning can automatically generate learning paths based on individual differences in each learner's learning preferences, goals, and other aspects, which is a good solution to the above problems [4, 5]. Therefore, accurate learning path recommendation can not only update and optimize according to the knowledge status of learners in the learning process, recommend learning paths for learners and track the learning status of learners, but also allow learners to clearly locate the direction of their own learning, for the goal of improving the efficiency and quality of learners' learning.

1.1. **Related work.** The traditional adaptive learning path recommendation model is based on the collaborative filtering recommendation algorithm (CFR). Yang et al. [6] combined the user's social network information and used the relevant rating information of friends to recommend personalized learning resources for the learners, and achieved a better recommendation effect. Salehi [7] introduced Learner Tree (LT) [8] by utilizing the relevant attributes of learning resources and learners as well as the sequential pattern of learners in accessing the recommended resources and utilized implicit and explicit based CFR to provide AL path recommendation service for learners to improve the recommendation quality. CFR generates cold start and data sparsity problems when performing AL path recommendation. And the recommendation model based on machine learning algorithm can alleviate the data sparsity issue through fusing multiple data sources and information. Zhang et al. [9] proposed a new model of full-path learning recommendation using machine learning technology, which first constructs a subject knowledge graph (KG) to predict the sequence of studying resources learnt through the learner and the studying performance during the learning process, and then selects a personalized learning full path from the predicted path results, with a recommendation accuracy of 82.9%. Wu and Feng [10] used fuzzy neural network to determine the best course learning path for students, but the recommendation error is large. Zhang et al. [11] adopted Bayesian network to realize the measurement of the current knowledge level of learners, and used TAN Bayesian network [12] to predict the learning style of learners to realize the learning path recommendation for different learners. Lin et al. [13] used decision trees (DTs) to implement AL path recommendation to achieve personalized learning path planning based on the learner's priority of the initial selection of learning content and the test scores after learning, but the recommendation is time-consuming.

The process of practicing recommendation models based on machine learning can be very time-consuming and requires a lot of data and computational resources. And intelligent optimization algorithms are widely used in the field of adaptive recommendation by narrowing down the search scope to quickly find a satisfactory solution or an approximate optimal solution. Ye et al. [14] applied the simulated annealing algorithm to AL path recommendation by introducing constraint fulfillment conditions to recommend learning paths by combining the knowledge of pre-keys that have not been absorbed and mastered by the learners. Benmesbah et al. [15] offered a Genetic Algorithm (GA)-based AL recommender system, which takes into account the difficulty of the courseware and the conceptual continuity in the learning path to rank the course content and improve the recommendation accuracy. Vanitha and Krishnan [16] used Ant Colony Algorithm (ACO) for AL content recommendation to improve the effectiveness of learning path recommendation by using the evaluation of learning objects by users with similar learning styles as a pheromone and further examining the evaluation of learning paths by a group of learners in the pheromone updating process. Liu et al. [17] fused the KG fusion particle swarm algorithm for AL content recommendation, which achieves personalized learning resources recommendation through dynamic synergistic adjustment of inertia weights and population diversity.

1.2. Contribution.

In summary, existing studies cannot comprehensively analyze learners' personalized characteristics, resulting in low recommendation matching and low recommendation accuracy. For this reason, this paper proposes a smart recommendation model of AL path for vocational ability education. The innovative work of the model is mainly reflected in the following four aspects.

(1) The OSKG architecture is designed to mine knowledge points and various attribute information, complete entity extraction and entity alignment, and establish relationships between entities by combining rule-based relationship extraction techniques.

(2) Construct a learner model from the three dimensions of basic attributes, learning styles, and cognitive levels, build a mathematical model of knowledge point path planning based on the learner model, take the constructed objective function as the fitness value of the AL path, and use the improved PSO to solve the objective function.

(3) PSO optimization (NFVBPSO) using nonlinear factors and viscous binary pairs with a chaotic strategy during population initialization to improve the quality of the population. The viscous weights are optimized adopting a nonlinear decreasing strategy, which better balances the algorithm's ability to explore between global and local.

(4) Mapping the learner model into OSKG as the starting point of path planning, taking the learning objective as the end point of path planning, solving the objective function through NFVBPSO to get the optimal knowledge learning path, and sorting and filtering the related resources to finally get the recommended sequence collection of learning resources.

The experimental results imply that the suggested model has better convergence speed and stability, and the recommendation accuracy is improved by 1.52%–14.86% compared to the comparison methods, which can better meet the learners' needs and present a better recommendation matching.

2. Theoretical analysis.

2.1. Concepts related to adaptive learning paths.

Adaptive Learning System (ALS) is a learning system that can visually present studying resources that meet the learning needs of learners at the right time according to their individualized characteristics [18]. ALS focuses on learners' learning styles, learning preferences and cognitive levels, and provides individualized learning solutions and learning approaches that enable learners to be fully self-directed. A traditional ALS consists of a runtime level, a storage level, and an intra-component level [19], as shown in Figure 1. The runtime layer mainly realizes the interaction of the system and presents information. The storage layer is used to store nodes and connections, and is the database of the ALS. The intra-component layer is the content of hypertext nodes.

An AL path is a sequential sequence of learning resources through which a learner carries out learning activities in order to accomplish a predetermined learning goal. AL path planning service refers to the process of generating the required learning resources for learners in the Internet environment, and providing personalized resource sequencing services by planning the learning resources in an orderly manner according to the characteristics of learners. By mining the learner's behavioral log data during learning activities and combining the learner's learning style to serialize learning activities, a learning path based on learning behavioral activities is formed, as shown in Figure 2.

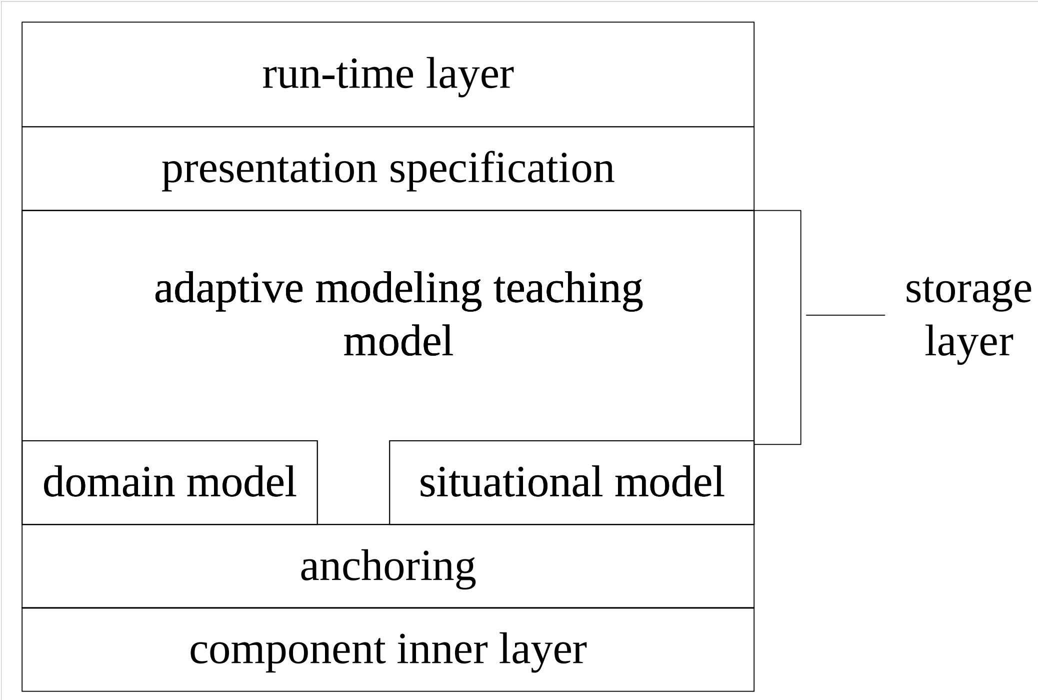


Figure 1. Traditional ALS structure

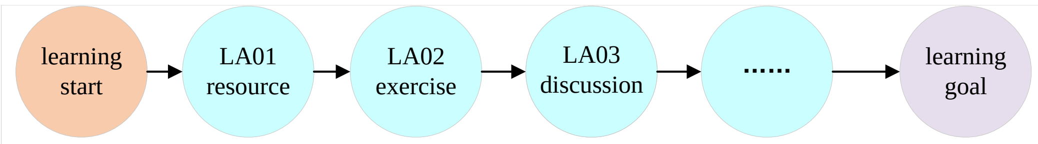


Figure 2. A learning path based on learning behavioral activities

2.2. **Particle swarm algorithm.** Researchers have proposed various methods to construct AL paths, such as decision tree classifiers [20], Markov decision processes [21], hierarchical task networks [22], and intelligent optimization algorithms, etc. Among them, intelligent optimization algorithms do not require complex theoretical foundations, provide learners with appropriate learning paths, and have a significant impact on solving the problem of learning object sequencing [23]. Commonly used intelligent optimization algorithms are GA, ACO, and PSO, etc. PSO has a simple concept and relatively easy programming implementation, and is able to jump out of the local optimal solution with strong global search capability through the particle's speed and position update mechanism. After years of research and development, PSO has proven to be effective in practical applications with good computational and convergence properties.

In the PSO algorithm, assume that there is an N-dimensional search space with population size M, and the specific position of particle i in the N-dimensional space can be represented by the coordinates $X_i = (x_{i1}, x_{i2}, \dots, x_{iN}), \quad i = 1, 2, \dots, M$. The position of each particle has the potential to be a solution to the final problem. Each particle is located at a position that has the potential to be a solution to the final required problem. The i-th particle will have a certain velocity, denoted as $V_i = (v_{i1}, v_{i2}, \dots, v_{iN}), \quad i = 1, 2, \dots, M$, during its motion. The optimal solution found by a single particle i during the search process is denoted as $P_i = (p_{i1}, p_{i2}, \dots, p_{iN})$, $i = 1, 2, \dots, M$, while the optimal solution found by the current swarm is $P_g = (p_{g1}, p_{g2}, \dots, p_{gN})$. Initially the PSO algorithm updates the particle states as shown in Equation (1) and Equation (2).

$$v_{in} = v_{in} + d_1 r_1 (p_{in} - x_{in}) + d_2 r_2 (p_{gn} - x_{in}) \tag{1}$$

$$x_{in} = x_{in} + v_{in} \tag{2}$$

For the goal of improving the proficiency performance of PSO, researchers have introduced inertia weights w to update the particle states, whose value is a non-negative number as shown in Equation (3).

$$v_{in} = w\, v_{in} + d_1 r_1 (p_{in} - x_{in}) + d_2 r_2 (p_{gn} - x_{in}) \tag{3}$$

3. **Construction of a knowledge graph for vocational competency education.** In order to better realize the AL pathway intelligence recommendation model, this paper designs a knowledge graph (OSKG) architecture of “Occupational Skills - Knowledge Points - Learning Resources”, utilizes the Chinese word segmentation tool [24] and the word vector similarity computation method to complete entity extraction and entity alignment, and combines with the rule-based relational extraction to establish the relationship among entities. The technical framework of OSKG is shown in Figure 3.

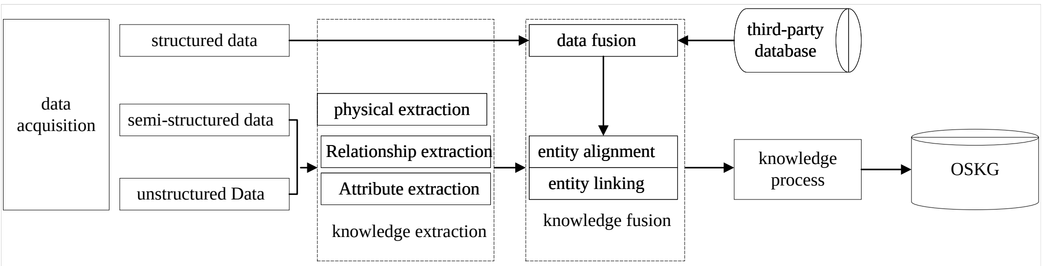


Figure 3. The technical architecture of OSKG

Entities in OSKG include Professional Skills (PS nodes), Knowledge Points (kp nodes) and Learning Resources (LR nodes), and the “Name” attribute is added to Professional Skills. The knowledge point has “name” and “grade” attributes, and the “grade” attribute is used to mark the complex degree of the knowledge point. The more sub-knowledge points the knowledge point contains, the greater the “grade” attribute value. The attributes of learning resources include name, type, and duration. All three entities have dependency and inclusion relationships. After the OSKG is constructed, the NLPIR-ICTCLAS Chinese lexicalization method [25] is firstly used to process the lexicalization and lexical labeling of the learning resources, and the nouns are extracted to form the noun set to be matched. Based on the dictionary of domain knowledge points in the literature [26] for entity matching, e_1 and e_2 are defined as the entity pairs to be matched, and the Word2vec model is trained to generate n-dimensional word vectors $\boldsymbol{\omega}$ and $\boldsymbol{\nu}$, and the cosine value between the vectors is calculated according to Equation (4), which is used as the similarity between e_1 and e_2.

$$\mathrm{sim}(e_1, e_2) = \cos\theta = \frac{\boldsymbol{\omega} \cdot \boldsymbol{\nu}}{\|\boldsymbol{\omega}\|\,\|\boldsymbol{\nu}\|} = \frac{\sum_{i=1}^{n} \omega_i v_i}{\sqrt{\sum_{i=1}^{n} \omega_i^2}\,\sqrt{\sum_{i=1}^{n} v_i^2}} \tag{4}$$

where ω_i, v_i are the values of dimension i in the word vector. Set the matching threshold ϕ, judge the interval in which the similarity of e_1 and e_2 is located to complete the entity matching, and determine whether the noun to be matched refers to a knowledge point in the domain.

$$\begin{cases} \text{sim}(e_1, e_2) \geq \phi \Rightarrow e_1, e_2 \text{ match}, \\ \text{sim}(e_1, e_2) < \phi \Rightarrow e_1, e_2 \text{ mismatch}. \end{cases} \tag{5}$$

By removing stop words and irrelevant words as mentioned above, the knowledge points are categorized. Due to the complexity of inter-entity relationships, domain experts define the template of inter-entity relationships in advance, match the text with the template, and finally use the neo4j graph database to complete the knowledge storage of knowledge point entities and entity relationships. The constructed OSKG contains all the knowledge points and relationships between knowledge points in the field of vocational ability education, which lays the foundation for the subsequent AL recommendation model.

4. **Learner modeling for vocational competency education.** After obtaining the OSKG, it is necessary to build a corresponding learner model (LM), which aims to truly reflect learner characteristics, such as knowledge and skill objectives, preferences and cognitive level, and convert them into data that can be understood by the computer, which will serve as a basis for the subsequent design of the recommendation model. In this paper, LM is constructed from the basic attributes of learners, learning styles and cognitive levels, as shown in Figure 4.

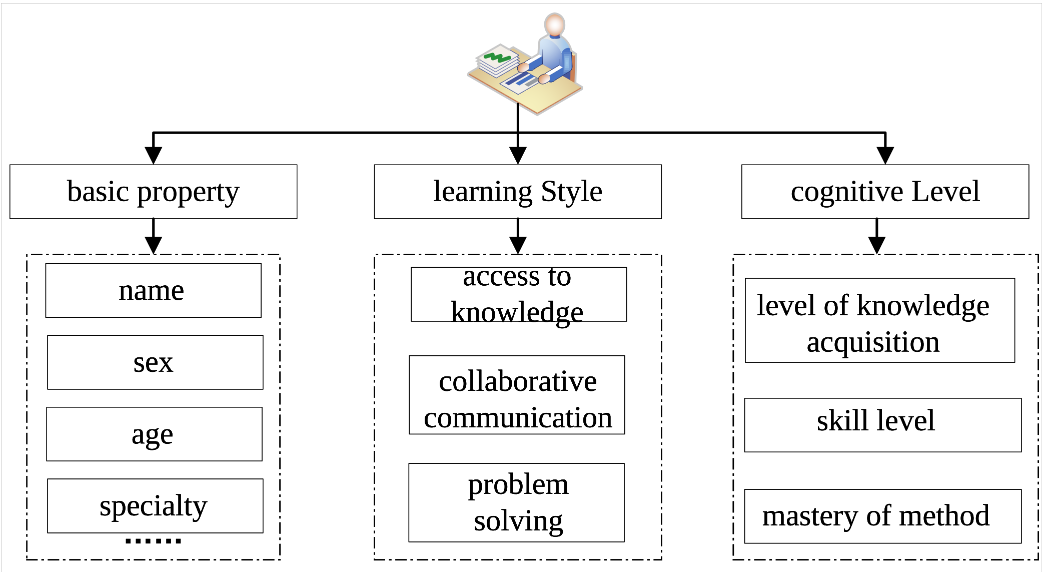


Figure 4. The constructed learner model

(1) Define learner S, model S as $S = (B(S), P(S), C(S))$, where $B(S)$ is the basic attributes of S, such as name, major, etc., and consider the group tendency in the learning process of S. Refine the big data of learner's studying process and analyze the studying style features, such as learning style preference and cognitive characteristics.

(2) According to Kolb's theory, studying styles are categorized into divergent thinking, absorptive, convergent thinking and adaptive, defining the studying styles of K learners, $LS = \{ls_1, ls_2, ls_3, \ldots, ls_k\}$, ls_k, as the style type of the k-th learner, $ls_k = \{ls_{k1}, ls_{k2}, ls_{k3}, ls_{k4}\}$, where ls_{k1} is the matching value of divergent thinking, ls_{k2} is the matching value of absorptive thinking, ls_{k3} is the matching value of convergent thinking, ls_{k4} is the matching value of adaptive, and the learner prefers to learn in whichever learning style. The learning style that the learner favors is represented by the largest matching value in that style, and satisfies $\sum_{q=1}^{4} e_q = 1$.

(3) A quantitative representation of S's cognitive level on N vocational skills knowledge points in the domain using $C(S) = \{c_i \mid i \in [1, N]\}$. The value is calculated during the learning process based on the learner's pre-tests, learning behavior data, etc., and a continuous value of 0 to 1 is used to distinguish between different levels of cognition.

5. An adaptive learning path intelligence recommendation model for vocational competency education.

5.1. Mathematical modeling of adaptive learning path planning. Based on the learner model constructed above, this paper designs an AL path wisdom recommendation model for vocational ability education, firstly, we establish a mathematical model of knowledge point path planning by combining the cognitive characteristics of learners, use the ideas of nonlinear factor and viscous binary for PSO optimization (NFVBPSO), optimize the knowledge point path by using the NFVBPSO to get an optimal solution of the learning path, and finally, based on the sequence of knowledge points and the learner model, the associated resources are sorted and filtered to obtain a sequence collection of learning resources. The entire structure of the suggested recommendation model is indicated in Figure 5.

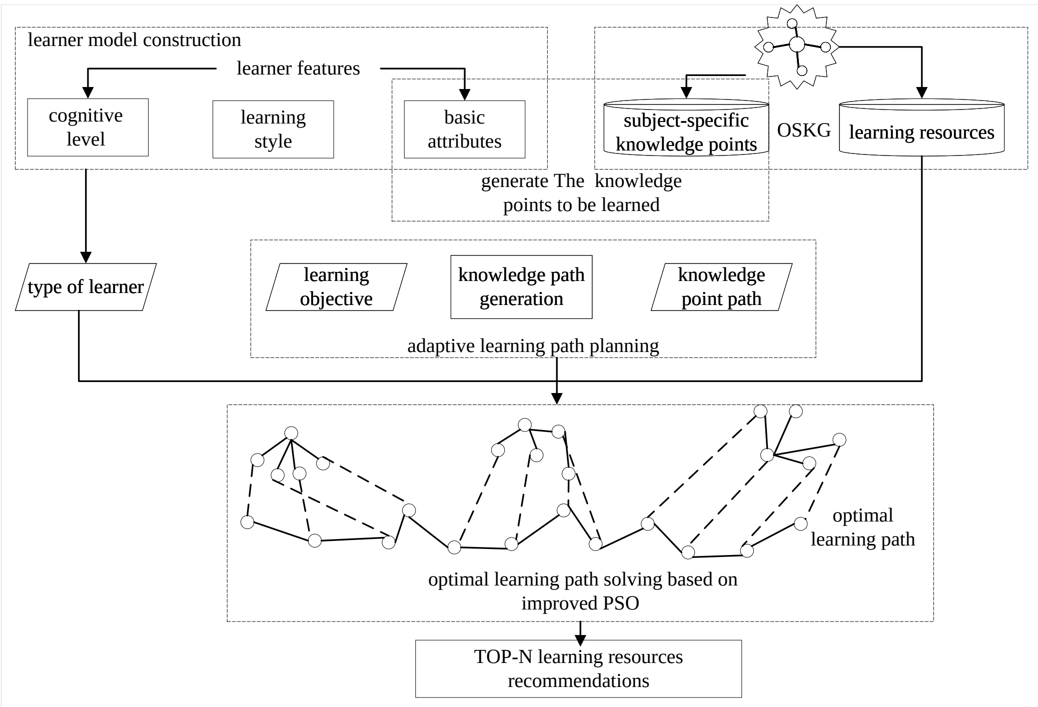


Figure 5. The overall structure of the proposed recommendation model

To ensure that learners grasp all prior knowledge points before learning a certain knowledge point, knowledge points are arranged according to the principle of importance from high to low, so as to minimize the overall learning cost. The objective function of this problem is defined as knowledge point path connectivity (KPC).

$$\mathrm{KPC} = \sum_{i \neq j} x_{ij} d_{ij} \tag{6}$$

where X is the knowledge point learning path selection matrix, when k_i to k_j is on the optimal path, $x_{ij} = 1$, and when k_i to k_j is on the normal path, $x_{ij} = 0$. D_K is the knowledge point relationship matrix, and matrix element d_{ij} is the connectivity between k_i and k_j. Its value is defined as follows.

$$d_{ij} = \frac{\text{Degree}\, k_j}{\text{ShortestPath}(k_i, k_j)} \tag{7}$$

The shortest path distance from k_i to k_j is $\text{ShortestPath}(k_i, k_j)$. The shorter the distance, the closer the connection between the two knowledge points. If the two knowledge points belong to the same knowledge surface, it is considered that there is no order between the two knowledge points, and $\text{ShortestPath}(k_i, k_j)$ is set to 1. If there is no path between the two knowledge points or the two knowledge points are homogeneous, the shortest path is assigned to the penalization parameter C. The degree of the knowledge point, $\text{Degree}\,|k_i| = \text{in}\,|k_i| + \text{out}\,|k_i|$, where $\text{in}\,|k_i|$ is the in-degree of k_i and $\text{out}\,|k_i|$ is the out-degree of k_i. The higher the degree, the more important the knowledge point is in the OSKG.

5.2. **Optimal learning path solving based on improved PSO..** After obtaining the mathematical model of AL path planning, NFVBPSO is utilized to search for the optimal paths in the solution space. AL paths are discrete in nature, and the traditional PSO has less than optimal searching efficiency when dealing with discrete issues. Therefore, improvements are made according to the population start-up and the decreasing policy of the viscosity factor, which better balances the exploration capability of the NFVBPSO algorithm between global and local. PSO employs a common policy of linearly diminishing viscous weights, initiating a local exploration at the iteration's outset before effectively locating the global premier solution, thereby causing the approach to become trapped in a local premier solution. Thus, this article suggests a nonlinear factor (NF) to strive for a balanced performance between the method's exploration and exploitation abilities, as illustrated hereinafter, where t is the present amount of epochs, T is the maximum amount of epochs, and i_u and i_l are the maximum and minimum values of i, respectively.

$$i = i_l + (i_u - i_l) \times \exp\left(-20 \times \left(\frac{t}{T}\right)^6\right) \tag{8}$$

For the goal of enhancing the caliber of the population, the Logistic mapping approach [27] is utilized by NFVBPSO for initializing chaos, as illustrated below, where $x_t \in (0, 1)$, μ denote the chaos's degree, and as the value of μ increases, so does the degree of chaos.

$$x_{t+1} = \mu\, x_t(1 - x_t) \tag{9}$$

During PSO iterations, particles converge towards the optimal particle's position, which can impact their ability to leap out of local optimum traps. The PSO is enhanced by employing the ideal particle perturbation technique and the worst particle updating mechanism [28], with the goal of enhancing its search prowess in the final stages. Equations for enhancing the least fit particle are implied in Equation (10) through Equation (12).

$$x_{\text{worst}}(t) = \arg\max\left(\text{fit}(x_1(t)), \text{fit}(x_2(t)), \ldots, \text{fit}(x_N(t))\right) \tag{10}$$

$$E_{\text{worst}}(t) = x_i(t) + \text{rand}\left(x_j(t) + x_k(t)\right) \tag{11}$$

$$x_{\text{worst}}(t) = \begin{cases} E_{\text{worst}}(t), & \text{if fit}(E_{\text{worst}}) < \text{fit}(x_{\text{worst}}), \\ x_{\text{worst}}(t), & \text{otherwise.} \end{cases} \tag{12}$$

where x_{worst} represents the location of the least fit particle and $\text{fit}(x_N(t))$ is the fitness value of the particle. In the event that the fitness value of the updated particle is lower than that of the worst particle, the position of the worst particle will be updated to E_{worst}; otherwise, it will continue to be the worst particle's position. The presence of a global best solution in PSO directs the motion of all particles towards it, which results in their clustering together in the subsequent stages. Thus, depending on how tightly packed the population is, the position of the global optimal solution undergoes a slight perturbation to broaden its global search capabilities, and the equation for judging the degree of aggregation of the population is shown as follows.

$$\text{avg\_x}(j) = \frac{1}{N} \sum_{i=1}^{N} x[i][j] \tag{13}$$

$$\text{avg\_r} = \frac{1}{N} \sum_{i=1}^{N} \|x_i - \text{avg\_x}\| \tag{14}$$

where avg_x is the core location of N particles, and avg_r represents the mean separation between the particle and avg_x. When avg_r increases, the diversity among the population grows, resulting in lesser disruption to the global best solution, vice versa, produces more disturbance to the global best solution. The perturbation policy is indicated in Equation (15) and Equation (16).

$$Nbest(t) = \big(1 + \text{sign}(\text{rand} - 0.5)\ \exp(-\text{avg\_r})\big) \times Gbest(t) \tag{15}$$

$$Gbest(t) = \begin{cases} Nbest(t), & \text{if fit}(Nbest(t)) < \text{fit}(Gbest(t)), \\ Gbest(t), & \text{otherwise.} \end{cases} \tag{16}$$

where $Nbest(t)$ is the particle after interference, and if the fitness value of $Nbest(t)$ is lower than the fitness value before interference, the particle after interference is the globally optimal particle. Finally, if the number of iterations is reached or degradation behavior occurs, the iteration is stopped, otherwise continue to update the velocity and position of the particles, and output the current best solution as the sequence of knowledge point learning paths $\text{path}_k = \{Q_{p1}, Q_{p2}, \ldots, Q_{pm}\}$.

5.3. **Adaptive learning path wisdom recommendations.** Utilizing the knowledge point learning paths that have been generated, the inclusion relationship among studying resources and knowledge points, and the attribute characteristics of learning resources, the studying resources are arranged based on the sequence of knowledge points, in accordance with the principles of high to low importance, easy to difficult, and high to low learner interest, so as to minimize the overall learning cost. (1) The difference between the knowledge points covered by the learning resources and the knowledge points to be learned in the learner's learning path, RKF, is as follows.

$$\text{RKF} = \frac{\sum_{q=1}^{Q} \sum_{n=1}^{N} X_{nk}\, ID_q \left(C_{kq} - RC_{nq}\right)}{\sum_{n=1}^{N} X_{nk}} \tag{17}$$

where C_{kq} is the mastery of the q-th knowledge point by the kth learner, RC_{nq} is the coverage of the q-th knowledge point by the n-th learning resource, ID_q is the positional order of the q-th knowledge point in the sequence of learning paths, and X_{nk} is the decision variable.

(2) The differences between learners' learning styles and types of learning resources RTP are as follows.

$$\text{RTP} = \frac{\sum_{p=1}^{P} \sum_{n=1}^{N} X_{nk} \left|ST_p - RS_{np}\right|}{\sum_{n=1}^{N} X_{nk}} \tag{18}$$

where ST_p is the match between the kth learner and the p-th learning style type, $0 < ST_p < 1$, $\sum_{p=1}^{P} ST_p = 1$; RS_{np} is the match between the n-th learning resource and the p-th presentation type, $0 < RS_{np} < 1$, $\sum_{p=1}^{P} RS_{np} = 1$.

(3) The difference between the learner's ability level and the difficulty level of the learning resources RDP is as follows.

$$\mathrm{RDP} = \frac{\sum_{n=1}^{N} X_{nk} \left|T_k - D_n\right|}{\sum_{n=1}^{N} X_{nk}} \tag{19}$$

where T_k is the cognitive level of the k-th learner and D_n is the difficulty level of the nth learning resource. The weighted fusion of RKF, RTP, and RDP yields the learner-learning resource connectivity $\mathrm{Con}(S, R)$, as shown in Equation (20).

$$\mathrm{Con}(S, R) = w_{\mathrm{RKF}} \cdot \mathrm{RKF} + w_{\mathrm{RTP}} \cdot \mathrm{RTP} + w_{\mathrm{RDP}} \cdot \mathrm{RDP} \tag{20}$$

where $w_{\mathrm{RKF}}, w_{\mathrm{RTP}}$ and w_{RDP} are weight indicators and $w_{\mathrm{RKF}} + w_{\mathrm{RTP}} + w_{\mathrm{RDP}} = 1$, the N learning resources with the highest connectivity are recommended to learners.

6. **Performance testing and analysis.**

6.1. **Analysis of adaptive path recommendation results with improved PSO algorithm.** The experiments use the educational dataset of professional competence in computer science collected by Akhyar [29] on the educational platform junyiacademy.org, which contains 13645 learner records, and the ontology of knowledge in the field of computer science obtained by constructing relevant professional skills and knowledge point concepts in the positions of JAVA WEB programmer, Mysql database operation and maintenance, and so on. It covers 1389 positions, professional skills and knowledge concepts and 4167 inter-conceptual relationships. In this paper, 80% of the data are arbitrarily chosen as the training set, 10% as the validation set, and 10% as the test set to conduct the experiments. In the experiment, the population size is $N = 30$, and the maximum number of iterations is $T = 200$. According to the a priori experience, the upper limit of the viscosity value is T 10 , and the lower limit is T 10 0 ; the upper limit of the adaptive factor is 10 N , and the lower limit is zero.

Recommendation results may be affected by the number of learners and knowledge points, so this paper sets up two groups of experiments to analyze the recommendation results, Experiment 1 (E1), Experiment 2 (E2) is to keep the number of learners unchanged, the number of knowledge points gradually increased; Experiment 3 (E3), Experiment 4 (E4) is to keep the number of knowledge points unchanged, the number of learners gradually increased. The mean *avg* and variance *var* of the optimal values obtained after 100 runs of the model were used as evaluation metrics. The experimental outcome of the proposed models NFVBPSO and GAALS model, ACOLS model and PSOAL model on the objective function are shown in Table 1. From E1 and E2, it can be seen that as the amount of knowledge points increases, the mean and variance of NFVBPSO in this problem model show a decreasing trend, indicating that the results of its optimization search are more accurate. From E3 to E4, it can be seen that as the number of learners increases, the mean and variance generated by NFVBPSO decreases. It shows that the method obtains better results both with the increase in the number of learners and the increase in the number of learning resources.

Figure 6 shows the convergence graphs of the experiment. Where (a) and (b) denote the convergence graphs of E1 and E2, the convergence speed and stability of NFVBPSO increases gradually with the increase of the number of knowledge points. (c) and (d) show the convergence curves of E3 and E4, with the increase in the amount of learners, the convergence speed and stability of NFVBPSO also works better than other algorithms. Thus, both with the increase in the number of knowledge points and the number of learners, NFVBPSO better meets the needs of learners and presents a better recommendation matching.

Table 1. Experimental results of different models on the objective function

Experiment	Index	GAALS	ACOLS	PSOAL	NFVBPSO
E1	avg	6.5878	6.6328	4.6187	4.3406
	var	5.8548	5.2479	5.1398	4.4735
E2	avg	3.4822	3.7481	2.6458	1.8552
	var	4.2158	3.5667	3.1849	1.5251
E3	avg	3.6179	3.0046	2.4136	1.8336
	var	7.4944	5.5367	2.8125	2.1306
E4	avg	5.2517	4.2638	3.8085	1.1415
	var	4.9615	3.7384	1.6689	1.1123

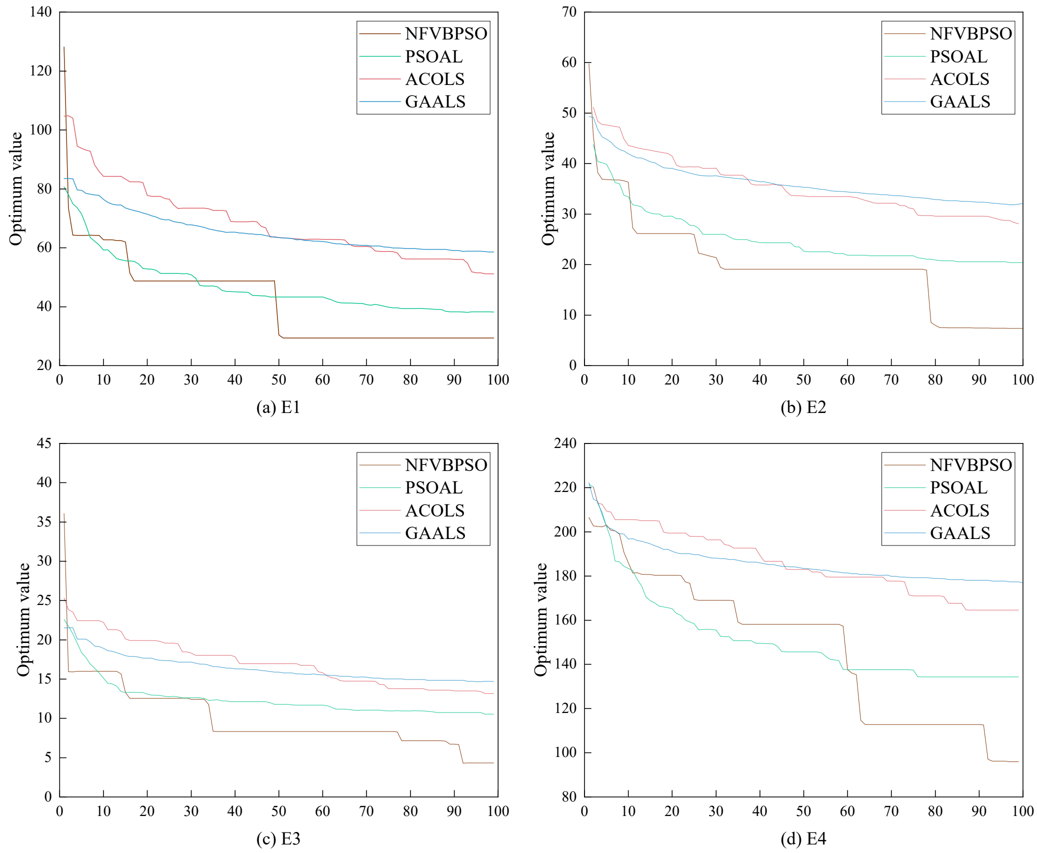
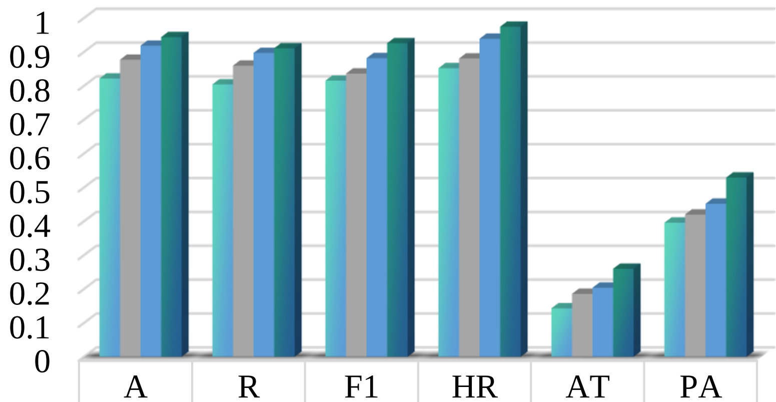


Figure 6. The convergence graphs of the experiment

6.2. **Performance analysis of adaptive learning path recommendation.** In order to further validate the recommendation performance of NFVBPSO, the precision-related metrics Accuracy (A), Recall (R), F1, and Cumulative Hits (HR), and the non-precision-related metrics Adaptation (AT), and Personalization (PA) [30] are selected in this paper to measure whether the recommended learning resources meet the learner's characteristics. When the number of learning resources is taken as 100, the comparison of performance metrics of different methods is shown in Figure 7.

The A, R, and F1 of NFVBPSO are 0.9436, 0.9105, and 0.9257, respectively, which are improved by 1.52%–14.86% compared with GAALS, ACOLS, and PSOAL, and NFVBPSO can realize more accurate recommendation. The HR of GAALS, ACOLS, and PSOAL are 0.8519, 0.8805, and 0.9388, which is at least 3.63% lower compared to NFVBPSO. NFVBPSO not only constructs the learner model and establishes the objective function of AL paths, but also uses the optimized PSO to solve for the optimal paths, which improves the accuracy of recommendations. Comparing the non-precision metrics AT and PA again, NFVBPSO improves at least 17.16% over GAALS, ACOLS, and PSOAL. Although GAALS uses GA to optimize the learning paths, GA requires coding and cross-variance operations, which results in a more complex algorithm. ACOLS uses ACO for AL path recommendation, but it is very easy to fall into local optimum, which affects the convergence speed. PSOAL optimizes the learning path by PSO, but it does not improve PSO, so the recommendation performance is not as good as that of NFVBPSO. In a word, NFVBPSO not only provides suitable learning resources, but also achieves a better recommendation result.



	A	R	F1	HR	AT	PA
GAALS	0.8215	0.8041	0.8152	0.8519	0.1428	0.3958
ACOLS	0.8769	0.8593	0.8361	0.8805	0.1857	0.4196
PSOAL	0.9183	0.8969	0.8814	0.9388	0.2038	0.4516
NFVBPSO	0.9436	0.9105	0.9257	0.9742	0.2596	0.5289

GAALS ACOLS PSOAL NFVBPSO

Figure 7. The comparison of performance metrics of different methods

7. **Conclusion.** This paper offers an AL path intelligent recommendation model for vocational competence education to address the issues of low matching between existing recommended personalized learning paths and learners' needs and low recommendation accuracy. Firstly, OSKG is designed, the knowledge points and various attribute information are mined, the entity extraction and entity alignment are completed, and the relationship between entities is established by combining the rule-based relationship extraction technology. Secondly, the LM is constructed so as to truly reflect the learner characteristics. According to the LM, a mathematical model of knowledge point path planning is established, and the improved PSO is used to solve the objective function. Then, using the nonlinear factor and viscous binary pair optimization of PSO (NFVBPSO), the learner model is mapped into OSKG as the starting point of path planning, and the learning target is taken as the end point of path planning, and the optimal AL path is obtained by solving the objective function through NFVBPSO to get the set of recommended sequences of learning resources. The experimental outcome implies that the proposed model presents better recommendation matching and recommendation accuracy both with the

increase in the number of knowledge points and the increase in the number of learners. Although the proposed model achieves good recommendation results, OSKG has problems such as complexity of construction, expertise of knowledge, and dependence on the amount of data, and it is necessary to capture the dynamic evolution of the learner's own knowledge system and optimize the efficiency of processing large amounts of data when providing personalized services. In the subsequent work, this paper will further improve the construction of OSKG, incorporate data such as learner behavior, and optimize the recommendation algorithm to enhance the recommendation performance.

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