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RESEARCH ON INTEGRATING BLOCKCHAIN AND MACHINE LEARNING LPP ALGORITHM IN ONLINE EDUCATION PLATFORM UNDER COVID-19 ENVIRONMENT

DAOJUN WANG, MEISHU WANG, AND XINLI XING*

Abstract. Learners confront the issue of navigating an enormous quantity of resources in the developing field of online education, which has been exacerbated by the COVID-19 pandemic. To solve this, our research proposes a novel Learner Path Planning (LPP) model that integrates blockchain and machine learning technologies to maximize the online learning experience. This model employs the ant colony optimization technique, which has been upgraded with blockchain for enhanced security and machine learning for intelligent path planning, to provide a more personalized and efficient learning experience. Our approach determines the extent of concept realization and interaction by examining the interaction degrees of knowledge points, establishing heuristic information and initial pheromone levels for the optimization process. This technique not only optimizes teaching duration based on instructional efficacy, but it also adapts dynamically to individual learner needs. Our empirical data reveal that goal success rates improve significantly across all learner levels. For example, elementary students in 2021 had the highest goal achievement rate of 0.5896. In 2019, intermediate and advanced learners attained rates of 0.7726 and 0.9058, with a significant association between course similarity and target achievement. Blockchain integration ensures secure and transparent processing of educational data, while machine learning algorithms successfully personalize learning routes to meet the various demands of learners. This study not only assists learners in effectively identifying suitable resources, but it also provides useful insights for instructors in improving online teaching approaches. The model's adaptability and scalability make it particularly applicable in the context of the COVID-19 pandemic's rapid developments and problems in the education sector.

Key words: COVID-19; Online education platform; Ant colony optimization algorithm; Learner behavior characteristics; Path planning

1. Introduction. Corona Virus Disease 2019 (COVID-19), as an acute respiratory infectious disease, is a threat to the economic development and life safety of people all over the world. In the context of the rampant COVID-19, many industries such as education, retail, engineering and finance have been seriously impacted. This has led to many offline work not being carried out normally. With the wide application of information technology, online education platform came into being in this context, and has been vigorously developed. It not only enabled students to harvest massive teaching resources, but also fundamentally changed the way learners acquire knowledge. It will no longer be constrained by objective conditions such as place, time and space [1, 2]. In recent years, new educational forms such as Muke have changed the original teaching methods. Learning management system and other high-quality learning platforms provided new possibilities for learners [3, 4]. The learning behavior data in the online learning platform can be used to analyze the learning effect through big data technology, thus promoting the teaching process [5, 6].

In order to enhance learners' efficiency and effect, many education experts have discussed learning path planning (LPP) algorithms. But learners' learning abilities vary greatly. Therefore, finding a satisfactory learning path is a major and challenging task. At present, LPP algorithms can be divided into two types, namely, planning the learning path of a course and planning the learning path between courses. Ant colony optimization algorithm has strong adaptability and robustness. It shows good performance in dealing with many problems. A LPP algorithm based on multidimensional time series data analysis is proposed. It is expected to promote the in-depth integration of education and teaching and modern information technology, and provide technical support for the wide application of intelligent education.

The rapid expansion of online education, spurred by the COVID-19 pandemic, has given the educational sector with new prospects as well as obstacles. One of the most significant issues for learners utilizing online platforms is resource overload. While abundant learning tools are valuable, they might overwhelm learners,

*Department of Physical Education, Qingdao Agricultural University, Qingdao 266109, China (Corresponding author, Xinli_Xing2023@outlook.com)

impeding effective learning and route planning. This circumstance involves a novel strategy to streamlining the online learning process, guaranteeing that learners may efficiently access and use resources adapted to their specific needs and learning objectives. In this context, the incorporation of blockchain and machine learning technology into Learner Path Planning (LPP) algorithms is a game changer. Blockchain technology, which is well-known for its security, transparency, and decentralized nature, provides a solid framework for managing educational data. At the same time, machine learning delivers cognitive analytical skills, which are critical for personalizing the learning experience based on individual learner profiles and behaviors.

The study makes a significant contribution to the field of online education technology in various ways:

1. We created a model that blends blockchain and machine learning with the LPP algorithm. This connection provides secure and effective resource management while also personalizing the learning route for each learner.
2. Our model effectively navigates the enormous array of online resources by incorporating ant colony optimization techniques into the LPP algorithm. This strategy effectively directs learners to the most relevant and valuable content, enhancing their learning experience.

2. Related works . COVID-19 has had a huge impact on the education industry. Online education in colleges and universities has become a hot research topic for educators. Learner behavior data is of great significance for analyzing learning habits, learning status and cognitive level, and can also improve teaching quality. Su G et al. found that there is great variability between learners' learning behavior and test results by visualizing learners' learning behavior. This is helpful for teachers to monitor the course progress and learners' learning performance, and timely adjust teaching strategies according to the actual situation [7]. Zhao Y and other researchers proposed a learning habit determination and LPP method based on learning behavior analysis. This method planed and recommended the path of learning content according to learners' learning habits [8]. Liu Y, et al., studied the characteristics of learners' learning activities and learning habits, and compared the importance of these characteristics through experiments. The results showed that the characteristics related to learning habits play a more important role in predicting students' performance [9]. Li J proposed a new adaptive network learning model based on big data. First of all, the model used genetic algorithms to evaluate learners' relevant future education goals. Then, the adaptive personalized learning path was generated by combining the ant colony optimization algorithm. Finally, social network analysis was used to determine learners' motivation to assign learning rhythm to each learner [9].

Wang J et al. built an improved adaptive tutoring system model using ant colony optimization algorithm, which can find the best learning path according to the learning mode and performance of the improved adaptive tutoring system [11]. Zhang J scholars and researchers classified learners' learning styles. Ant colony optimization algorithm was used to help learners find adaptive learning objects to obtain the best learning path [21]. Cui Z proposed a learning path optimization method based on evolutionary algorithm. The context of each knowledge point, the learning interests of learners and the fields involved in learning resources were comprehensively considered to extract the relationship between knowledge. Based on the evolutionary algorithm, the objective function was optimized, and the learning path to meet the learning needs of learners was finally constructed [22]. Zhou X et al. proposed an adaptive learning model based on ant colony algorithm. This can meet learners' different preferences and knowledge levels, and help improve learners' academic performance and learning efficiency [14]. Yang Y et al. proposed the research method of online learning resource serialization by analyzing the characteristics of learning resource serialization, and modeling it at different stages. And based on the learning needs of learners, combined with particle swarm optimization algorithm, the intelligent seriation service system of learning resources was built [15].

From the relevant research status of online education platform and LPP algorithms, there are three kinds of LPP algorithms that are common and widely used at present. They are data mining, association rules and other algorithms, LPP algorithm based on graph theory, intelligent bionic algorithm, etc. However, the existing LPP algorithms are difficult to achieve good learning results. This is embodied in the interaction between learners, the role of interaction between teachers and learners in LPP, the failure to consider the review of knowledge points in the learning, and the failure to reflect the role of learning habits in LPP and effect. The research used multidimensional time series data analysis method to construct LPP algorithm, with a view to making corresponding contributions to the improvement of teaching effect in online education platform.

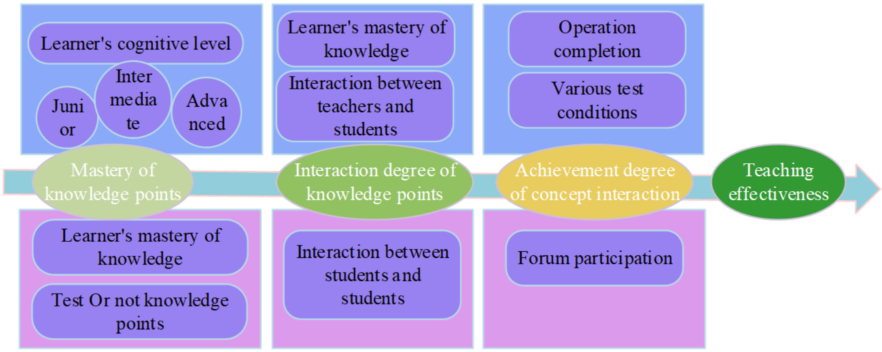


Fig. 3.1: Relevance Between Related Definitions

3. Construction of LPP Algorithm in Online Education Platform.

3.1. Definition of LPP Algorithm and Improvement of Ant Colony Optimization Algorithm. LPP algorithm plays a key role in improving teachers' teaching quality and students' learning effect. In order to obtain the optimal learning path of learners and in a relatively short time, a LPP algorithm based on ant colony optimization and multidimensional time series data is proposed. The algorithm defines the degree of realization of concept interaction by the degree of knowledge point interaction. This sets the heuristic information and initial pheromone of the ant colony optimization algorithm according to the degree of concept interaction and learning path. At the same time, it also optimizes the teaching duration according to the teaching effect to help learners obtain good learning effect [16-18]. To better describe the algorithm-related models, the research first describes the algorithm-related definitions. In view of the different cognitive levels of learners, they are divided into three levels: primary, intermediate and advanced. The definitions related to the algorithm include the mastery of knowledge points, the interaction degree of knowledge, the realization of concept interaction, and the teaching effect. Figure 3.1 refers to the relevance between related definitions.

After learners get corresponding scores through online test items, researchers can obtain the mastery of knowledge according to the test results. However, previous studies only considered untested and tested knowledge points. On this basis, the study considers the learners' mastery of knowledge points, and the detailed steps are as follows. The matrix S can be regarded as the test scores of m learners on the k test questions, that is, formula 3.1.

$$S=\begin{bmatrix} s_{11} & \cdots & s_{1m} \\ \vdots & \ddots & \vdots \\ s_{k1} & \cdots & s_{km} \end{bmatrix} \tag{3.1}$$

The matrix F is the correlation between$k$test questions and n knowledge points, which can then determine whether students' mastery of knowledge points can be tested in the test questions, that is, formula 3.2.

$$F=\begin{bmatrix} f_{11} & \cdots & f_{1k} \\ \vdots & \ddots & \vdots \\ f_{n1} & \cdots & f_{nk} \end{bmatrix} \tag{3.2}$$

In formula 3.2, the value of F in the research process is 0, 1, 2, and 3, and the degree of association is no association, partial association, indirect association, and direct association. After obtaining matrix S and matrix F , we can get the learner u's mastery of knowledge point i , which can be referred to by formula 3.3.

$$mkp_{u,i}=\frac{\sum_{j=1}^{J} f_{ij}\cdot s_{uj}}{\sum_{j=1}^{J} f_{ij}\cdot \text{score}_j} \tag{3.3}$$

J is the number of exercises of test knowledge point$i$in formula 3.3. The correlation value of test question j and knowledge point i is f_{ij}. The test score of test question j is S_{uj} , and the test score of test question j is $score_j$. After the collaborative analysis of the interaction behavior data and learning behavior of learners at different levels, the research can obtain the interaction degree of knowledge points according to the interaction degree between students, the system interaction degree of learners, and the interaction of educators and students. Formula 3.4 refers to the interaction degree of learners to knowledge points $ikp_{u,j}$.

$$ikp_{u,j} = \alpha_1 \cdot SC_{u,i} + \beta_1 \cdot SS_{u,i} + \gamma_1 \cdot SS_{u,i} \tag{3.4}$$

In formula 3.4, the degree of systematic interaction between learner u and knowledge point i. The degree of interaction between learners, and the degree of interaction between teachers and students are denoted by $SC_{u,i}$, $SS_{u,i}$ and $SC_{u,i}$ respectively. According to the relevant introduction results of the references, the weight coefficient $(\alpha_1, \beta_1, \gamma_1) = (0.36, 0.33, 0.31)$ is shown below.

$$\begin{cases} SC_{u,i} & = \alpha_2 \cdot f_{SC_{u,j}} + \beta_2 \cdot t_{SC_{u,j}} + \gamma_2 \cdot p_{SC_{u,j}} \\ SS_{u,i} & = \frac{\sum_{v=1}^{m-1} w_{SS_{uv,i}} \cdot f_{SS_{uv,i}}}{m-1}, \quad u \neq v \\ SS_{u,i} & = \frac{w_{ST_{u,j}} \cdot f_{ST_{u,j}} + score_{u,j}}{\sum_{u=1}^{m} score_{u,j}} \end{cases} \tag{3.5}$$

In formula 3.5, the number and duration of the learner u to the knowledge point i are $f_{(SC_{(u,j)})}$ and $t_{(SC_{(u,j)})}$ respectively, and the number of times the learner u pauses and drags the progress bar to the knowledge point i is $P_{(SC_{(u,j)})}$. Research results of references, $(\alpha_2, \beta_2, \gamma_2) = (1, 5, 4)$. The interaction weight coefficient and interaction times of learner u and v to knowledge point i are and respectively, the weight coefficient and interaction times of learner to knowledge point are $f_{(ST_{(u,j)})}$ and $f_{(ST_{(u,j)})}$ respectively, and the homework test score of learner u to knowledge point i is $score_{u,j}$. Conceptual interaction attainment refers to the interaction between new and old concepts in learners' minds, which is difficult to obtain directly. According to the actual situation of online education development, conceptual interaction can be indirectly expressed through forum participation and other ways [19-20]. In order to accurately define the learners' understanding of knowledge points, the is defined by combining the degree of interaction between knowledge points and the learners' mastery of knowledge points, as shown in formula 3.6.

$$c_{kp_{(u,i)}} = \frac{mkp_{(u,i)}}{ikp_{(u,i)}} \tag{3.6}$$

In formula 3.6, the learner u's mastery of knowledge point i is $mkp_{(u,i)}$, and the learner u's interaction with knowledge point$i$is $ikp_{(u,i)}$. The learning effect of learners is directly related to the duration of video knowledge points and the degree of concept interaction. The learning effect of learners'u on the knowledge point i is referred to by formula 3.7.

$$TE_{(u,i)} = \frac{ckp_{(u,i)} \cdot T_i}{T} \tag{3.7}$$

In formula 3.7, the duration of video knowledge points i is T, and the total duration of n video knowledge points of the course is T . The teacher sets the teaching duration of learners at different levels according to the course objectives, and obtains the teaching effect of all learners in the U_c level on the knowledge points according to the learning effect, that is, formula 3.8.

$$TE_i = \frac{1}{m_c} \sum_{u=1}^{m_c} TE_{(u,i)} \tag{3.8}$$

In formula 3.8, the number of U_c learners is m_c.

As an intelligent bionic algorithm, ant colony optimization algorithm has many advantages, such as heuristic search, strong robustness, positive information feedback, self-organization, distributed computing, and so on. It is often used to find the best path. Figure 3.2 shows the principle of ant colony optimization algorithm.

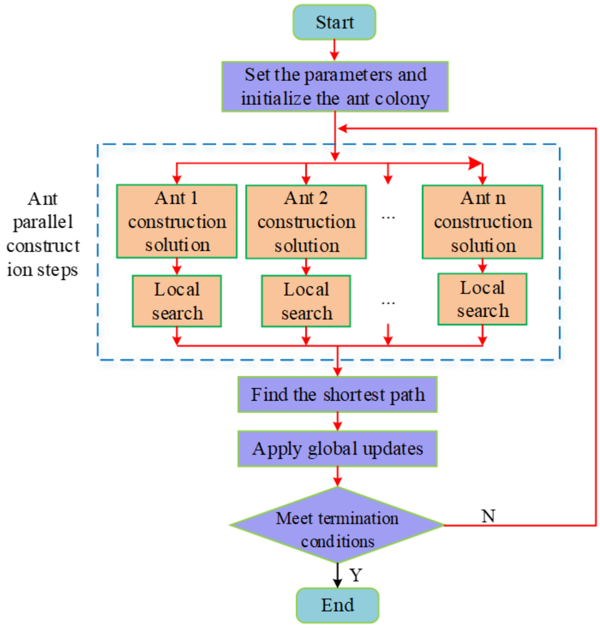


Fig. 3.2: The Principle of Ant Colony Optimization Algorithm.

Ant colony optimization algorithm actually simulates the ability of ants to find the shortest feeding path through information exchange. Ants secrete pheromones during foraging, which completes information exchange between ant groups. The calculation expression of pheromone increment is very important for the update of pheromone. There are three commonly used models for pheromone increment, namely, ant perisystem model, ant quantity system model, and ant density system model [21, 22, 23]. The first two pheromone increment models use local information to update pheromones after a node transfer. The latter pheromone increment model uses global information to update the pheromones passing through the path after each iteration. In order to further improve the performance of ant colony optimization algorithm, scholars in relevant fields have improved it. The ant colony optimization algorithm is improved by using optimization sequencing and elite strategy. Combining the advantages and disadvantages of the two ant colony optimization algorithms, the strategy to improve the ant colony optimization algorithm is optimized sorting. The algorithm sorts ants according to the path length to obtain the ranking order of each ant. The pheromone weighted update method is the ranking order of ants. The shorter the path length is, the higher the ranking order of the ants is, and the larger the weight value is. The pheromone update is required for the ants in front. The calculation formula is as follows 3.9.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij} + \sum_{k=2}^{w} \Delta\tau_{ij}^{k}(t) + \Delta\tau_{ij}^{*}(t) \tag{3.9}$$

In formula (9), the initial pheromone volatilization factor is ρ, and its value range is (0,1). The ants from the 2nd to the w place updated the pheromone as $\sum_{k=2}^{w} \Delta\tau_{ij}^{k}(t)$, and the best ants updated the pheromone as $\Delta\tau_{ij}^{*}(t)$.

3.2. Learning Path Optimization Algorithm Using Multidimensional Time Series Data and Ant Colony Optimization Algorithm. From the definition of learning path optimization algorithm, the construction of learning path optimization algorithm is described. Because the carrier of knowledge points is course videos, the essence of learning path is to sort the learning order of learners' course videos according to their behavior characteristics. Figure 3.2 is the flowchart of the algorithm. First of all, the interaction degree

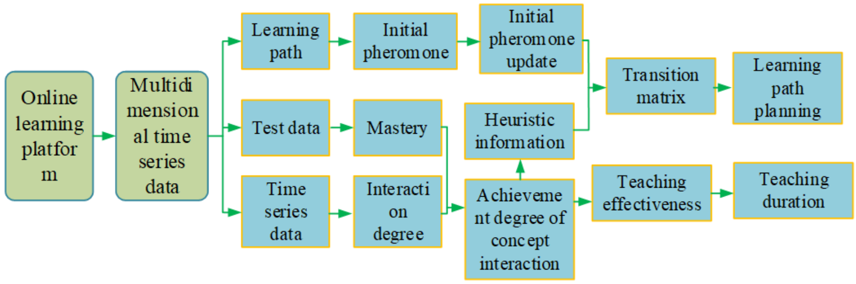


Fig. 3.3: Flow Chart of LPP Optimization Algorithm Based on Multidimensional Time Series Data and Ant Colony Optimization Algorithm

and mastery degree of knowledge points are obtained by analyzing the multi-dimensional time series data of learners in the online learning platform. According to the relevant calculation formula, the teaching effect and concept interaction attainment of learners at different levels are calculated. Then, the learning path of the prior learner is represented by the directed weight graph. The initial pheromone τ_{ij} is obtained by using ant colony optimization algorithm. The heuristic information η_{ij} is obtained according to the degree of realization of concept interaction. The initial information is updated by the learner's score ranking, the time to complete the knowledge points, and the length of the learning path. Heuristic information and pheromone are used to obtain the learner's transfer matrix P . According to the learner's transfer matrix P , it is need to select the next knowledge point to learn after learning the current knowledge point by comparing the transfer value. Finally, the learning paths planned by learners of different levels are obtained. At the same time, the teaching duration is optimized according to the effect that learners of different levels want to achieve.

The teacher cannot assure that the curriculum objectives are effectively achieved by presenting all students with a uniform video knowledge point learning length and learning path. As a result, the online education platform must incorporate earlier pupils' cognitive levels. This allows students to learn in the course based on the course objectives, learning needs, and personal advantages. The learning path of a priori learner can be expressed by formula 3.10.

$$W = [w_{ij}]_{n\times n} \tag{3.10}$$

In formula 3.10, the number of times the learner has learned i and j according to the sequence is w_{ij}. The initial pheromone between two knowledge points is related to the number of learning paths of learners. If the number of learning paths is more, the higher the initial pheromone left on the learning path can be considered, and the calculation is formula 3.11.

$$\tau_{ij} = w_{ij} \tag{3.11}$$

The heuristic information η_{ij} can reflect the heuristic preference of transferring from the current knowledge point i to the next knowledge point j. The heuristic information set in the study is related to the learning situation of learners, and the calculation is formula 3.12.

$$\eta'_{ij} = ckp_{ij} \tag{3.12}$$

In formula 3.12, the higher the value of η_{ij}, the better the effect is that learners continue to learn knowledge point j after completing knowledge point i. In the path planning learning process, the initial pheromone update depends on the appropriate parameter selection [24, 25]. The initial pheromone of learners mainly depends on the following three factors, namely, the score ranking of learners, the time spent in completing the learning of knowledge points, and the length of learning path. The relevance of knowledge points and compactness in the

Table 3.1: 2018-2021 Settings of Three Levels and Three Levels of Parameters

Grade	2019			2020			2021		
	p		k	p		k	p		k
Primary	0.15	1.60	0.65	0.45	2.50	1.70	0.05	0.75	0.40
Intermediate	0.15	1.45	3.00	0.25	1.50	1.70	0.20	0.95	2.80
Senior	0.15	0.50	2.60	0.30	0.65	3.00	0.25	1.15	1.50

teaching process should be considered. The calculation of $\Delta\tau^*_{ij}(t)$ is formula 3.13.

$$\Delta\tau^*_{ij}(t) = \begin{cases} \alpha_3 \cdot (m_c - R) \cdot w_{ij} \cdot TE_{(u,j)} + \beta_3 \cdot \frac{t_j}{T_j} + \gamma_3 \cdot \frac{l}{L} & \text{if } u \in (i,j) \\ 0 & \text{otherwise} \end{cases} \tag{3.13}$$

In formula 3.13, the score of the learner u is$R$, the individual learning effect and duration of the learner on the knowledge point are TE_{uj} and t_j , respectively. The video duration of the knowledge point is . The total path length of the learner is , and the original video path length is . According to the research results of many scholars, the value of $(\alpha_3, \beta_3, \gamma_3)$ is (0.34,0.33, 0.33). The transfer matrix can complete LPP for learners of different levels, which can be used in $P = (P_{ij_{n\times n}})$. According to the learning situation of learners, the transfer value of learning knowledge point after learning knowledge point i is equation 3.14.

$$p_{ij} = \begin{cases} [\tau'_{ij}]^\lambda \cdot [\eta'_{ij}]^k & \text{if } i \in (i,j) \\ 0 & \text{otherwise} \end{cases} \tag{3.14}$$

In formula 3.14, the heuristic information and pheromone of path(i, j) are referred to by $\tau_(ij)$ and, and the parameters λ and k refer to the influence of these two factors on the transfer value respectively. The optimization of teaching duration needs to be combined with the teaching effect and cognitive level of learners. The calculation formula is formula 3.15.

$$T'_i = \left(\frac{1}{TE_i}\right) \Bigg/ \left(\sum_{i=1}^{n} \frac{1}{TE_i}\right) \cdot T \tag{3.15}$$

For the optimization of teaching duration and learning path, the transfer matrix of each learner is calculated based on the multi-dimensional time series data and the learners' directed weight diagram. Then select the maximum transfer value of the knowledge point by comparing the transfer value of the unified level learners, and judge whether the selection of the next knowledge point is abnormal. The learning times of current knowledge points is judged by the number of knowledge points. Based on this, it needs to select the next knowledge point and observe the learners' transfer matrix to obtain the optimal learning path of learners' cognitive level. Finally, the teaching duration is optimized according to the teaching effect of learners. The data selected for the study is the multi-dimensional time series data generated by the Shanghai School during the learning process of 2018-2022 level-4 learners. The indicator of learners' learning is the degree of achievement of curriculum objectives. First of all, it needs to compare the degree of achievement of the overall objectives and sub-objectives of the courses for learners at different levels from 2019 to 2021. It selects the best grade from the same grade according to the engineering certification results. The optimal learning path is obtained according to the given algorithm. Then, it analyzes the learners' multidimensional time series data to optimize the duration of video knowledge points. The length of video knowledge points and the best learning path are recommended to the 2022 beginner, intermediate and advanced learners. Finally, the effectiveness of the algorithm is verified according to the learning situation of 2022 learners [26, 27, 28]. Table 3.1 refers to the settings of three levels and three levels of parameters in 2018-2021.

4. Performance and Effect Analysis of Learning Path Optimization Algorithm. There are three forms of assessment for the course "Logical Structure and Algorithm" selected in the study. It has a different

Table 4.1: Assigned Value of the Assessment Method Corresponding to the Course Sub-Objectives

Course sub-objectives	Assessment method 1 (70%)	Assessment method 2 (20%)	Assessment method 3 (10%)	Target score	Equivalent score
1	20	20	20	60	20
2	20	20	20	60	20
3	30	30	30	90	30
4	30	30	30	90	30

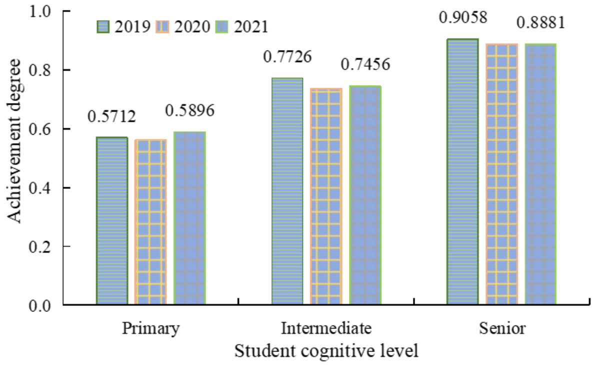


Fig. 4.1: Achievement of the Overall Objectives of Different Grades of Courses

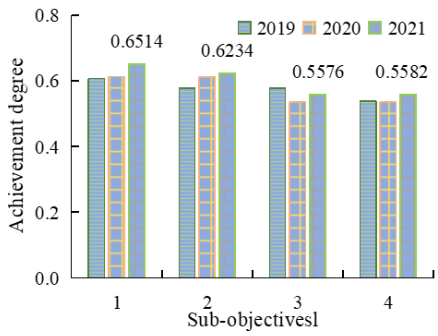
proportion in the achievement of the overall goal of the course, and is used as the basis to evaluate whether the learners have passed the assessment. The course has four objectives. They are to examine students' ability to apply basic theories and methods, judge students' ability to accurately describe the process of dealing with complex engineering problems, and evaluate students' comprehensive technical requirements. The ability to design modules and solutions to meet specific needs, and the ability to analyze students' ability to summarize and correlate complex engineering problems. Table 4.1 refers to the distribution value of the assessment method corresponding to the course objectives.

Figure 4.1 shows the achievement of the overall objectives of different grades of courses. For the same grade, the higher the cognitive level of learners, the higher the degree of achievement of the overall goal of the curriculum. For primary learners, the overall goal achievement rate of 2021 learners is the highest, with a value of 0.5896. For intermediate and advanced learners, the overall goal achievement of 2019 learners is the highest, with values of 0.7726 and 0.9058 respectively.

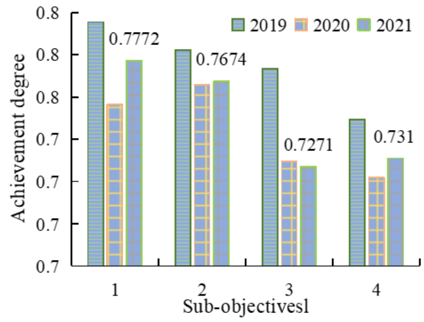
Figure 4.2(a) - (c) refers to the degree of achievement of the objectives of the primary, intermediate and advanced courses. For junior learners, except that the degree of achievement of sub-goal 3 in 2019 is higher than that in 2021, the degree of achievement of other sub-goals in 2021 is the highest; Intermediate learners have the highest degree of achievement of the four courses in 2019; Advanced learners achieved the highest level of sub-objectives in 2019, except that the sub-objectives in 2019 were lower than those in 2021.

Therefore, the research will analyze the time series data generated during the learning process of 2018 level junior, 2016 level intermediate and advanced learners. Figure 4.3(a) - (c) shows the optimal path for different learners. Green, yellow and red refer to learners appearing once, twice, three or more times in the path planning. The path planned by primary learners is short and simple; The path complexity of intermediate learners' planning is related to learners' ability in view of the relationship between junior and senior learners; The path planned by advanced learners is long and complex.

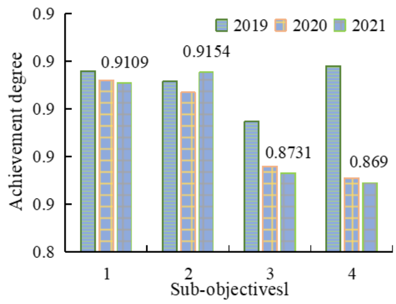
Figure 4.3(a) - (c) refers to the comparison between the optimized teaching duration and the original duration of primary, intermediate and advanced learners. The effect of some knowledge points in education is poor, and the duration has obvious changes. The teaching duration optimized by different levels of the



(a) junior learners



(b) Intermediate learner



(c) Advanced learners

Fig. 4.2: Achievement of Objectives of Primary, Intermediate and Advanced Courses)

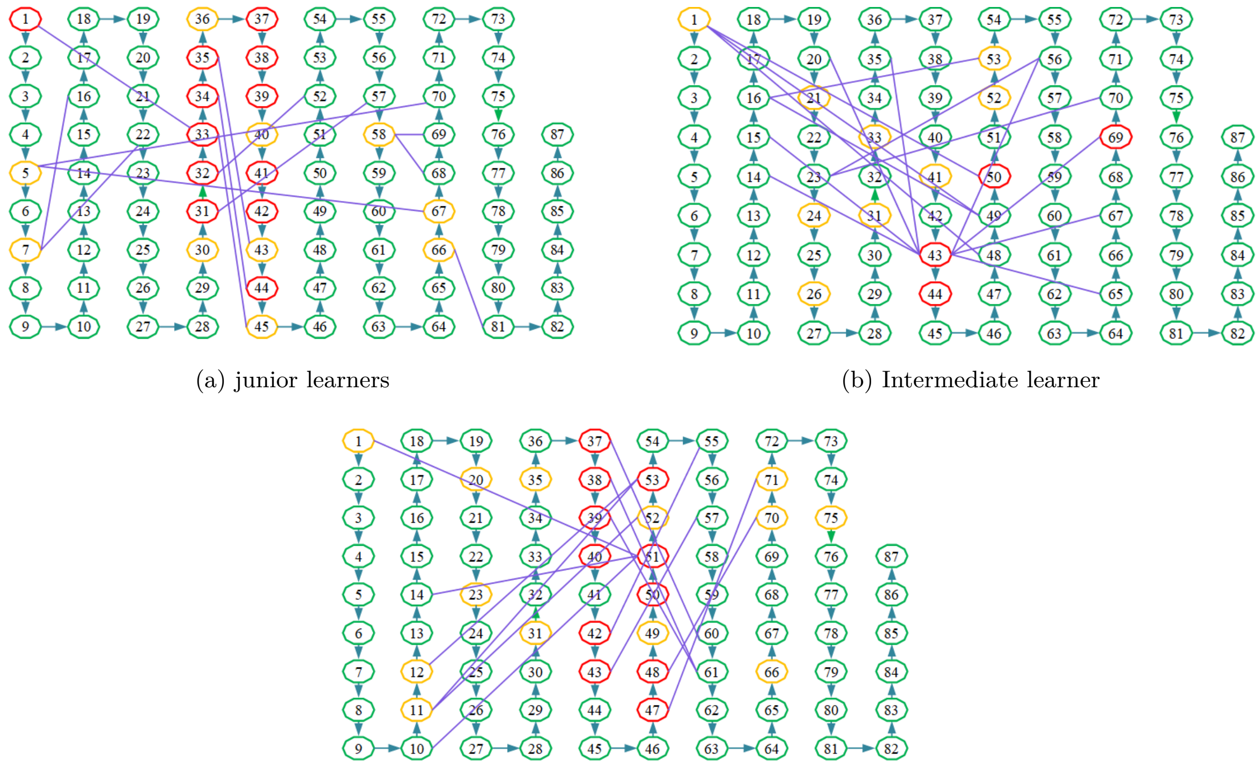
Table 4.2: Relationship Between the Original Video Duration of Some Knowledge Points and the Recommended Teaching Duration

Knowledge points	Original duration	Primary	Intermediate	Senior
26	500	152	147	177
28	371	191	185	229
31	157	1318	1391	1355
32	244	481	429	441
51	113	2131	1780	2152
57	462	117	130	152
89	149	1448	1376	1463

same knowledge points is different. The algorithm can optimize the teaching time of video knowledge points according to different cognitive levels of learning to meet learners' learning needs and improve learners' learning efficiency.

Figure 4.5 shows the relationship between the original video duration and the recommended teaching duration of some knowledge points. According to the actual teaching effect, there are obvious changes in the teaching duration planned by learners, such as knowledge points 26, 31, 89, etc. Different levels of learners have different learning abilities. Different from the teaching time planned by primary learners, the teaching time of most knowledge points planned by intermediate and advanced learners is shorter. The reduction ratio is about 15% and 20%.

Figure 4.5 shows the relationship between the achievement of the overall goal of the course and the similarity



(a) junior learners

(b) Intermediate learner

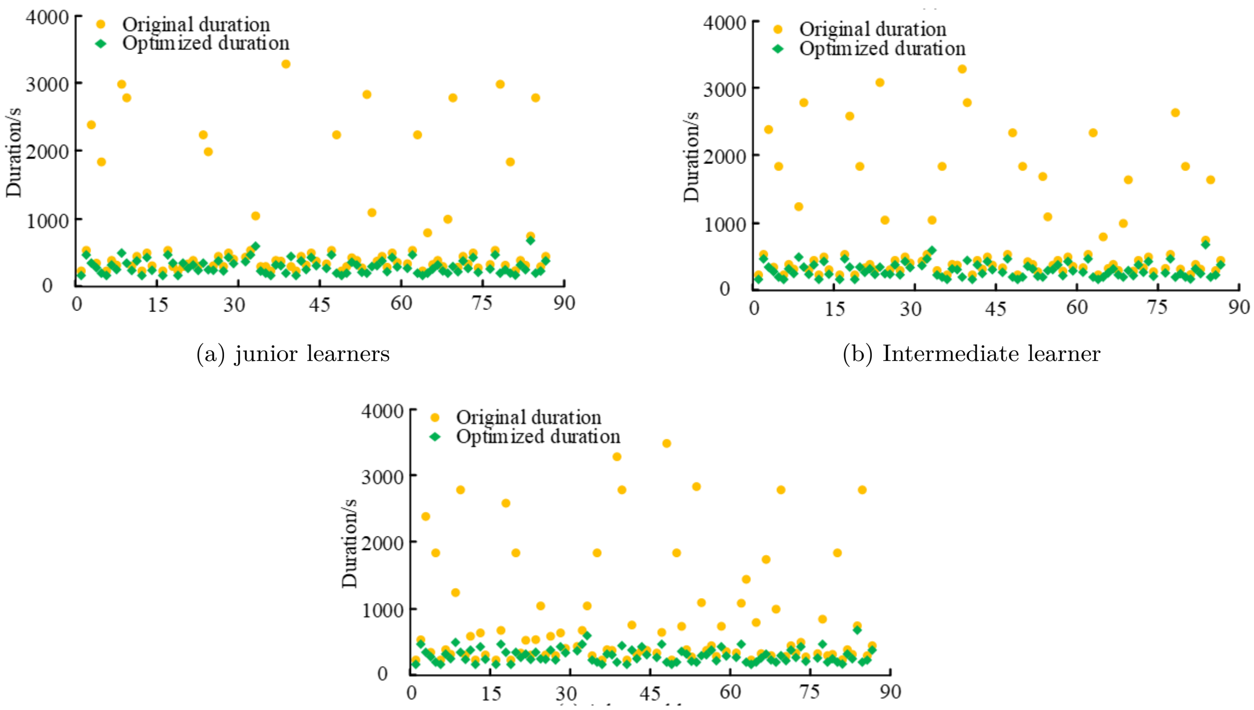
(c) Advanced learners

Fig. 4.3: The Best Learning Path for Different Learners)

of the learning path. For learners with the same cognitive level, the more similar the recommended path and learning path are, the better the overall goal of the course will be achieved. The algorithm given can improve the degree of achievement of the overall goal of the course and help learners to pass the course assessment. For intermediate learners, 40% 50% of the learners' overall course goal achievement degree slightly decreased, and the overall increase with the increase of similarity. The degree of achievement of the overall curriculum objectives of advanced learners increases with the increase of similarity.

Figure 4.6(a) - (c) refers to the relationship between the degree of achievement of curriculum objectives and the degree of similarity for primary, intermediate and advanced learners. Among the primary learners, the four course sub-objectives of the learners whose learning path similarity is less than 40% fail to meet the standard; Among the intermediate learners, except for the four courses with 40% 50% similarity, the degree of achievement of the sub-objectives has decreased, but the overall degree of achievement has increased with the improvement of the similarity; Among advanced learners, except the obvious decrease in sub-goal 1 of the curriculum, the achievement of sub-goal of the overall curriculum is in high degree.

5. Conclusion. To obtain the optimal learning path of learners in a relatively short time, a LPP algorithm based on multidimensional time series data and ant colony optimization was proposed. The path planned by primary learners was short and simple. The path complexity of intermediate learners' planning was related to learners' ability, considering the relationship between junior and senior learners. The path planned by advanced learners was long and complex. The teaching effect of some knowledge points was poor, and the duration had obvious changes. The teaching duration optimized by different levels of the same knowledge points was different. Different levels of learners had different learning abilities. Different from the teaching



(a) junior learners

(b) Intermediate learner

(c) Advanced learners

Fig. 4.4: Comparison Between Optimized Teaching Duration and Original Duration of Primary, Intermediate and Advanced Learners

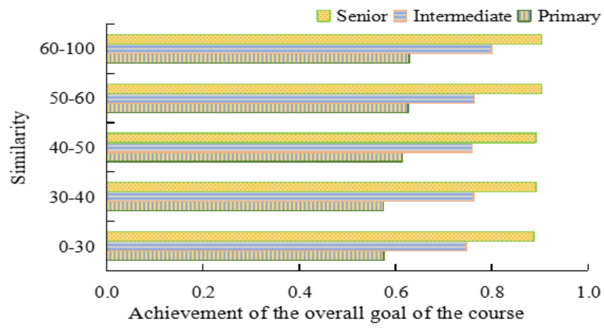
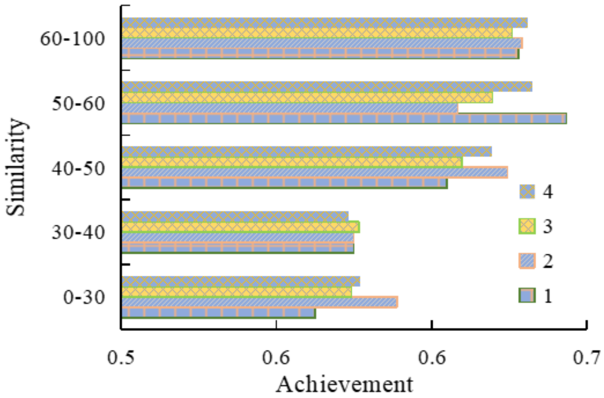
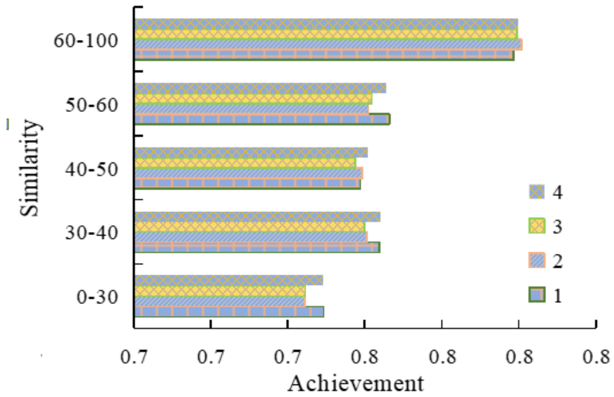


Fig. 4.5: the Relationship Between the Achievement of the Overall Goal of the Course and the Similarity of the Learning Path

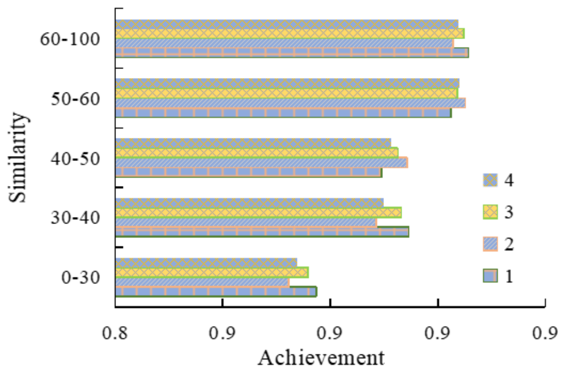
time planned by primary learners, the teaching time of most knowledge points planned by intermediate and advanced learners was shorter, with a reduction of about 15% and 20%. Among the primary learners, the four course sub-objectives of the learners whose learning path similarity was less than 40% fail to meet the standard. Among the intermediate learners, except for the four courses with 40% 50% similarity, the degree of achievement of the sub-objectives has decreased, but the overall degree of achievement has increased with the improvement of the similarity. Among advanced learners, except for the obvious decrease in sub-goal 1 of



(a) Junior learners



(b) Intermediate learner



(c) Advanced learners

Fig. 4.6: the Relationship Between the Degree of Achievement of Curriculum Objectives and the Degree of Similarity for Learners

the curriculum, the degree of achievement of sub-goal of the overall curriculum was high. For learners with the same cognitive level, the more similar the recommended path and learning path were, the better the overall goal of the course was achieved. The algorithm given can improve the degree of achievement of the overall goal of the course and help learners to pass the course assessment. The LPP algorithm given by the research plays a key role in improving the teaching quality of teachers and the learning effect of students. Future research could look into more advanced blockchain uses, such as smart contracts, to automate other educational processes, such as assessments and certifications.

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