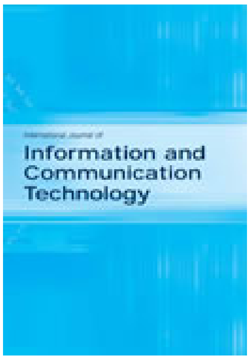

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A dynamic optimisation method for personalised learning paths integrated with knowledge graphs

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Abstract: As educational informatisation progresses, optimising personalised learning paths has become a focal point. Static learning paths cannot meet learners' diverse and dynamic needs. We present a dynamic personalised learning path optimisation approach using knowledge graphs. By leveraging knowledge graphs' association and representation, it analyses learner characteristics and learning resource attributes. Then, it builds a precise learning path model and monitors learners' real-time status. This allows dynamic adjustment of learning path node sequences and content presentation to fit individual learner differences. Experiments show it boosts learning efficiency, cuts learning time and error rates, and improves knowledge understanding. This study offers fresh ideas for personalised learning path optimisation, holding theoretical and practical importance. It can boost educational informatisation and aid in the personalised allocation and efficient use of educational resources.

Keywords: knowledge graph; personalised learning path; dynamic optimisation; educational informatisation; personalised allocation of resources.

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1 Introduction

With the rapid development of information technology, we have entered the information and intelligent era. Against this background, people are increasingly inclined to choose educational methods such as personalised learning and lifelong learning, and have put forward higher requirements for the diversity of educational resources and the flexibility of learning methods. Online learning, with its high flexibility and convenience, meets students' diverse learning needs and has become an important way for students to acquire knowledge. Students can independently choose their study time periods and locations based on their own needs, freely participate in courses, interact and communicate with teachers and students in real-time, and review key points of the courses at any time to consolidate their knowledge foundation (Zhu, 2023). These remarkable advantages have driven the vigorous development of the online education industry on the internet and have attracted widespread attention worldwide. However, the completely autonomous learning mode has also exposed some problems that need to be solved urgently. Although online learning platforms have gathered a vast amount of learning resources, they have also triggered the predicament of 'information overload', which poses a huge challenge for learners when screening resources that match their learning goals and ability levels. They often encounter learning obstacles due to the low compatibility of resources, and the learning efficiency is difficult to guarantee. Meanwhile, in the context of autonomous learning, learners are free from the supervision of traditional educational administrators. However, the in-depth analysis and precise control of the learning process by online learning platforms are still insufficient, which leads learners to be trapped in the predicament of 'getting lost in learning', trapped in a deadlock of vague learning direction, confused learning content and helpless learning methods (Li et al., 2023a). To address these challenges, online learning platforms are accelerating the integration of artificial intelligence technology and machine learning algorithms, deeply empowering personalised education practices. By precisely analysing multi-dimensional characteristics such as learners' cognitive levels, learning tendencies, and potential interests, the platform can comprehensively optimise the learning environment and enhance learning outcomes. Personalised learning path optimisation, as a key technology, not only solves the problem of learning resource discrimination by organising learning resources into an orderly sequence, but also lays out a clear and standardised learning advancement path for learners, comprehensively enhancing learning efficiency.

In order to achieve the dynamic optimisation of personalised learning paths, knowledge graphs and their graph embedding techniques are widely used to mine the semantic relationships between knowledge and construct efficient learning paths that meet learners' personalised needs (Li et al., 2023b). The knowledge graph embedding model TransE, put forward by Bordes et al. (2013), offers a fundamental starting point for path optimisation by transforming high dimensional sparse knowledge graphs into low dimensional dense vector spaces. This model has minimal parameters and modest computational complexity, and it delivers excellent performance and scalability when handling large scale sparse knowledge bases. Li (2021) utilised the practice answer records of learners, analysed the correlation of exercises through the Apriori algorithm, and then inferred the sequential learning relationship of knowledge points to construct the learning path. Yang and Wu (2009) combined the ant colony algorithm and dynamically adjusted the learning path based on the compatibility degree between the user's style and the learning resources. Niknam and Thulasiraman (2020) utilised ant colony algorithms to identify suitable course sequences as learning paths. Vanitha et al. (2019) blended ant colony and genetic algorithms, centring path planning on user learning goals and knowledge levels. Nabizadeh et al. (2020) located the course sequence by means of the depth-first search algorithm combined with learning objectives and knowledge graphs. Usually, self-designed topological sorting algorithms and optimisation algorithms are also adopted to serialise course resources based on the relationships and attributes among courses, and to plan the learning path from the perspective of knowledge structure to ensure learning efficiency. The multi-constraint learning path generation algorithm based on knowledge graph proposed by Zhu et al. (2018) solves the problem of learners choosing appropriate learning materials. Shmelev et al. (2015) combined genetic methods and knowledge graph technology to arrange course resources in sequence as learning paths. Pang et al. (2019) used knowledge graphs to reason out the sequential relationship of knowledge points, recommending subsequent knowledge to those who passed the learning and prior basic knowledge to those who failed, thereby forming a learning path. These studies provide a variety of technical means for the dynamic optimisation of personalised learning paths, but at the same time, they also face challenges brought by the scale and structural complexity of knowledge graph data, such as how to conduct path planning efficiently in large-scale knowledge graphs and how to dynamically adjust paths according to the characteristics of different learners. Future research can focus on how to combine deep learning technology to further enhance the representation ability of knowledge graphs and the performance of path optimisation algorithms, so as to better meet the needs of personalised learning.

This article focuses on the self-improvement oriented online learning model, taking the online courses on the online learning platform as the object, and conducts research around the optimisation of personalised learning paths. Aiming at the problems of 'information overload' and 'learning disorientation' faced by learners in this mode, a dynamic optimisation method for personalised learning paths integrating knowledge graphs is proposed. It aims to adapt to the individual differences and learning progress requirements of different learners by dynamically adjusting the node sequence and content presentation in the learning path, and provide learners with more accurate and efficient personalised learning paths. This can not only significantly improve learning efficiency, reduce learning time and error rate, and enhance learners' understanding and mastery of knowledge, but also provide new ideas and methods for optimising personalised learning paths. This holds theoretical weight and application potential. It is anticipated to foster growth in educational informatisation. Additionally, it is expected to assist in aligning educational resources more closely with individual needs and maximising their utilisation. Future research can further integrate deep learning technology to enhance the representation ability of knowledge graphs and the performance of path optimisation algorithms, so as to better meet the complex needs of personalised learning and create a more intelligent and personalised learning environment for learners.

The main innovations and contributions of this work include:

1 This paper innovatively proposes a new method for constructing learning paths by integrating knowledge graphs and learner portraits, breaking the limitation of traditional learning path construction that only relies on learners' static information and simple knowledge point associations. By deeply exploring the rich semantic relationships in the knowledge graph and the multi-dimensional features in the learner profile, accurately capturing the intrinsic connection between the individualised needs of learners and the knowledge system, constructing multi-dimensional personalised learning paths, providing learners with more precise learning guidance, and significantly enhancing the degree of personalisation in the construction of learning paths.

2 Aiming at the construction difficulty of learner portraits, this paper introduces the deep knowledge tracing (DKT) model to break through the limitation that the traditional way of constructing learner portraits is difficult to accurately depict the dynamic knowledge state of learners. The DKT model is based on the recurrent neural network (RNN) architecture. It conducts in-depth analysis of the interaction

behaviour sequence of learners on various knowledge points, accurately tracks the changes in learners' knowledge mastery during the learning process, and then constructs a learner profile that can dynamically reflect the knowledge level of learners.

3 In this paper, the particle swarm optimisation (PSO) algorithm is applied to the optimisation of personalised learning paths, and the parameter configuration and fitness function of the algorithm are redesigned to make it precisely adapt to the learning path optimisation scenario. The dynamic adjustment strategy of inertia weight is applied to enhance the global search ability of the algorithm. Meanwhile, the local search mechanism is introduced to improve the local mining ability, ensuring that the algorithm stably outputs high-quality learning paths in different learning situations. Compared with traditional optimisation algorithms, this method significantly improves the path adaptability and optimisation efficiency, providing strong technical support for personalised learning path optimisation.

2 Relevant technologies

2.1 Knowledge graph

To enhance information retrieval, Google developed a knowledge graph – a structured semantic network that represents real-world concepts and relationships using graph-based structures and symbolic formats. Typically built from subject-predicate-object (SPO) triples, each encodes factual knowledge in RDF format. RDF is a framework used to describe entities and the relationships between them. It represents nodes in a knowledge graph as 'entities' and edges as 'relationships' (Chen et al., 2020b). By subsequently applying knowledge-graph embedding techniques, (e.g., TransE, TransH, TransR), these triples are mapped into low-dimensional dense vectors, allowing the system to compute latent semantic similarities and sequential links between knowledge points – thereby uncovering the complex relationships required for effective personalised learning path optimisation. The knowledge graph is expressed as multiple 'entity-relation-entity' or 'entity-attribute-value' triples, structured into an ontology layer and a data layer. Among them, the ontology layer describes the main framework of the knowledge graph, defining concept classes, data attributes and object attributes; the data layer stores various types of data obtained from the data source. Based on this, the construction methods of knowledge graphs can be divided into top-down and bottom-up types. The bottom-up approach first constructs the data layer, conducts knowledge extraction from various data sources to generate triples, and performs knowledge fusion and knowledge processing. Then, the ontology layer is automatically constructed based on the data layer. The top-down approach is to first design the ontology model through domain experts, and then extract the data corresponding to the ontology and fill it into the data layer of the knowledge graph.

Knowledge graphs, as a kind of high-dimensional and sparse network structure, are not conducive to semantic computing among participating entities or relations, thus giving rise to numerous knowledge embedding methods. Throughout construction, accuracy is secured by cross-source triple fusion and automated conflict resolution, while timeliness is maintained through incremental updates that immediately absorb fresh learner-resource interactions into the data layer. Knowledge graph embedding (or representation learning) projects entities and relations into a low-dimensional space, modelling them as dense feature vectors (Chen et al., 2020a). For example, after embedding the knowledge graph of the discipline field, each knowledge point entity, etc. is represented as a floating-point type vector. By taking the vectors of any two knowledge points, the semantic similarity between these two knowledge points can be calculated. The process represents knowledge graph triples as (h, r, t), where h and t denote head and tail entities, and r their relationship. First, randomly initialise each named entity and relation into an n-dimensional vector format, which is the initial feature expression vector; the triples are split into training, test, and validation sets. The training set contains positive and negative samples, with their loss values computed using model specific score functions. The objective function minimises positive sample losses while maximising negative sample losses. Finally, entity and relation vectors are optimised through backpropagation using the objective function. Iterative training yields the final knowledge graph embeddings (Shen et al., 2022).

With its parameter efficiency and simplicity, TransE gained significant academic interest. This yields the scoring function in equation (1).

$$f(h, t) = \|h + r - t\|_2^2 \tag{1}$$

The TransE model's objective function uses positive triples S and generated negative samples S'. It minimises when $f(h, t) - f(h', t') > \gamma$, where $f(h, t)$ and $f(h', t')$ represent positive and negative sample scores respectively.

$$L = \sum_{(h,r,t)\in S} \sum_{(h',r,t')\in S'} \max\left(0, f(h, t) + \gamma - f\left(h', t'\right)\right) \tag{2}$$

However, since the TransE model is embedded only within one plane, it is unable to handle well the 'one-to-many' and 'many-to-many' relationships among entities. To make up for the deficiencies of the TransE model, the TransH model was proposed. In each triplet, relation r corresponds to a hyperplane. This model projects entities h and t onto the hyperplane corresponding to relation r for calculation. Different relations all have their own specific hyperplanes, which makes the same entity have different meanings under different relations. The specific projection method of the TransH model is shown as follows, where W_r represents the projection matrix of relation r.

$$h_\perp = h - W_r^T h W_r \tag{3}$$

$$t_\perp = t - W_r^T t W_r \tag{4}$$

The representation of relation r on its hyperplane is d_r. For the projected entities $h_\perp$, $t_\perp$, and relation d_r, during the training process of the TransH model, it is necessary to make $h_\perp + d_r \approx t_\perp$ as much as possible. Therefore, the scoring function is shown in equation (5).

$$f_r(h, t) = \|h_\perp + d_r - t_\perp\|_2^2 \tag{5}$$

Based on the score function, the objective function of the TransH model can be given as shown in equation (6).

$$L = \sum_{(h,r,t)\in S} \sum_{(h',r,t')\in S'} \max\left(0, f_r(h, t) + \gamma - f_r\left(h', t'\right)\right) \tag{6}$$

Unlike TransH, which projects entities into a shared relational space, TransR maps them into distinct spaces using separate projection matrices, resolving TransH's constraints. The TransR projection method is as follows.

$$h_r = hM_r \tag{7}$$

$$t_r = tM_r \tag{8}$$

The TransR model enforces $h_r + r \approx t_r$ for projected entities h_r, t_r and relation r during training, with its scoring function defined in equation (9).

$$f_r(h, t) = \|h_r + r - t_r\|_2^2 \tag{9}$$

Based on the score function, the objective function of the TransR model and the TransH model is the same. The basic idea is that if the score gap between positive and negative samples is greater than γ, the objective function can be minimised. Therefore, it will not be elaborated here.

2.2 Learner profile

Accurate assessment of learners' knowledge mastery can help construct a more precise learner profile and improve learning efficiency. The mainstream methods for evaluating Knowledge mastery include Bayesian knowledge tracing (BKT) technology and DKT technology (Thomas et al., 2023). BKT models learner knowledge states using binary variables. The probability distribution of variables is updated using the first-order Markov model to predict the learners' answer results. However, due to the overly simple and idealised representation of the knowledge state by the BKT technology, it has not been widely studied and applied. The DKT model adopts the RNN to represent and track the knowledge state of learners, and complete tasks such as predicting learners' answers and discovering the associations of exercises (Zhang et al., 2024). When evaluating the knowledge state of learners, the traditional RNN model is affected by short-term memory and is unable to convey the earlier knowledge state of learners. Long short-term memory (LSTM) uses the 'gate' structure to represent the cell state and performs the discarding and retention of new and old information between the 'gates', and performs well in long sequence training (Zhou et al., 2018). Gated recurrent unit (GRU) is an improvement of LSTM. GRU combines the forget gate and the input gate into the update gate z_t, and uses the reset gate r_t and the temporary state $\tilde{h}_t$ to complete the mixed operation of the cell state and the hidden state, reducing over-fitting and optimising the calculation process of the hidden layer state.

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1} + b_r\right) \tag{10}$$

$$\tilde{h}_t = \tanh\left(W_h x_t + U_h\left[r_t \otimes h_{t-1}\right] + b_h\right) \tag{11}$$

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1} + b_z\right) \tag{12}$$

$$h_t = \left(1 - z_t\right) \otimes h_{t-1} + zt \otimes \tilde{h}_t \tag{13}$$

DKT based on GRU networks characterises the knowledge state of learners as the hidden layer output in the network, effectively improving the evaluation accuracy and reducing the training and verification costs of traditional RNN networks. In this paper, combined with the response sequence of learners' exercise answers, the DKT input based on GRU networks is further optimised to evaluate their mastery of prior knowledge. The DKT model is selected over alternatives like BKT because its GRU-based recurrent architecture can continuously update mastery states from learners' interaction sequences, capturing dynamic knowledge evolution instead of relying on the static binary assumptions inherent in earlier models.

Behavioural science theory quantifies human characteristics through observable actions, and holds that human activities are an inevitable manifestation for achieving specific goals or tasks. Apply this theory to the field of online learning and develop the technology for analysing online learning behaviours. Statistical methods analyse learning behaviours using mathematical models, producing quantitative results through index scoring and chart evaluation. Index scoring links behaviours to learning outcomes via correlation analysis, while behavioural labels capture learner preferences for personalised recommendations. Similar learners are grouped using clustering algorithms like FCM, which calculates membership probabilities through iterative fuzzy set optimisation. For dataset X (n samples, c clusters), FCM minimises objective function J_{FCM}, where u_{ij} represents sample j^{th} membership in category i, c_j denotes cluster centres, and m is the fuzziness factor.

$$\min J_{FCM} = \sum\nolimits_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \left\| x_j - c_i \right\|^2 \tag{14}$$

$$s.t. \sum_{i=1}^{c} u_{ij} = 1,\ j = 1, 2, ..., n \tag{15}$$

The membership degree u_{ij} and the clustering centre c_j are iteratively calculated according to the above equation.

$$u_{ij} = \left[\sum_{k=1}^{c} \left(\frac{\left\| x_j - c_i \right\|}{\left\| x_j - c_k \right\|} \right)^{\frac{2}{m-1}} \right]^{-1} \tag{16}$$

$$c_j = \frac{\sum_{j=1}^{n} \left(u_{ij}^{m} \cdot x_j \right)}{\sum_{j=1}^{n} u_{ij}^{m}} = \sum_{j=1}^{n} \frac{u_{ij}^{m}}{\sum_{j=1}^{n} u_{ij}^{m}} x_j,\ 1 \le i \le n,\ 1 \le j \le c \tag{17}$$

$$\max\nolimits_{ij} \left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{k} \right| \right\} < \theta \tag{18}$$

2.3 PSO algorithm

PSO simulates bird flock behaviour to solve optimisation problems. Its simple implementation and few adjustable parameters make it effective for complex scenarios (Gad, 2022). For discrete problems, they later proposed binary PSO (BPSO) in 1997. While traditional PSO struggles with sequential constraints, BPSO excels at discrete optimisation like learning path planning. In BPSO, particle velocity updates combine inertia, self-learning, and social learning (Wang et al., 2018). The $t + 1$ generation position depends on both the t-generation position and $t + 1$ velocity vector, calculated as follows:

$$v_{ij}^{t+1} = \omega v_{ij}^{t} + c_1 r_1 \left(p_{ij} - x_{ij}^{t} \right) + c_2 r_2 \left(g_{ij} - x_{ij}^{t} \right) \tag{19}$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \tag{20}$$

Here, i denotes particle index, j denotes the dimension; ω is inertia weight; t is iteration count. Constants c_1 (self-learning) and c_2 (social learning) typically equal 2. Random numbers r_1, $r_2 \in [0, 1]$. p_{ij} and g_{ij} represent particle i's local best and global best solutions. BPSO defines motion probabilistically, with state transition probability given by:

$$X_{ij} = \begin{cases} 1, & rand() < S\left(v_{ij}\right) \\ 0, & rand() > S\left(v_{ij}\right) \end{cases} \tag{21}$$

$$S\left(v_{ij}\right) = \frac{1}{1 + e^{-v_{ij}}} \tag{22}$$

This paper proposes MABPSO, an improved PSO algorithm featuring adaptive nonlinear inertia weights and a mutation operator. The inertia weight increases nonlinearly with iterations, enhancing global optimisation and local escape capabilities in later stages. The mutation operator expands particle exploration, increasing diversity and improving local optimum avoidance. While smaller inertia weights boost exploration and larger ones favour exploitation, linear optimisation fails to balance these effectively. Thus, we optimise inertia weights nonlinearly to better reflect the algorithm's evolutionary state. The weight w per iteration is calculated as follows:

$$w = \begin{cases} \omega_{\min} + \dfrac{2}{\pi} \arctan\left(\pi * \dfrac{t\left(\omega_{\max} - \omega_{\min}\right)}{T} \right), 0.4 < \omega \le 0.9 \\ \omega_{\max}, \omega > 0.9 \end{cases} \tag{23}$$

Here, t represents the number of iterations and T represents the maximum number of iterations respectively. Take $w_{\max} = 0.9$ and $w_{\min} = 0.4$.

To enhance convergence and prevent premature stagnation, we incorporate a genetic algorithm inspired mutation operator into the binary PSO. The modified algorithm is defined as:

$$v_{ij}^{k+1} = w v_{ij}^{k} + c_1 r_1 \left(p_{ij} - x_{ij}^{k} \right) + c_2 r_2 \left(g_{ij} - x_{ij}^{k} \right) + \rho r_3 \left(Random - x_{ij}^{k} \right) \tag{24}$$

3 Learning path optimisation model framework

3.1 Personalised learning path optimisation

To optimise personalised learning paths, one must first represent the characteristics of learners and learning resources mathematically. Individual learner differences are explicitly encoded by feeding DKT-estimated mastery levels and multi-dimensional learner profiles into the weights of f1–f4, so that each objective function is dynamically scaled to the learner's current cognitive stage and weak knowledge points. This involves expressing each characteristic as a mathematical symbol and constructing a function to link them, forming the optimisation function for personalised learning paths (Zheng et al., 2022). Four learner characteristics are key: cognitive ability, current learning resource information, target knowledge point information, and effective learning time. Learning resources also have four key characteristics: resource difficulty, resource information, contained knowledge point information, and resource specific learning time (Jiang et al., 2022). The optimisation function consists of four objective functions, labelled f_1 to f_4.

The objective function f_1, termed the learner's cognitive alignment goal, quantifies the gap between a learner's cognitive capacity and the complexity of learning resources. A minimised value indicates that the resource difficulty in the suggested path is well matched to the learner's cognitive stage, as detailed in equation (25).

$$f_1 = \sqrt{\sum_{j=1}^{N} \left| \frac{\sum_{i=1}^{N} \left[X_{ar_i br_j} \left(d_{ar_i} - c_h \right) + X_{ij} \left(d_{br_j} - c_h \right) \right]}{2 \sum_{i=1}^{N} ar_i br_j} \right|^2}, 1 \le h \le H \tag{25}$$

The objective function f_2, known as the learner expectation target, measures the disparity between the knowledge points within learning resources and those that learners aim to acquire. A smaller disparity means the resources better align with learners' knowledge acquisition goals, as outlined in equation (26).

$$f_2 = \frac{\sum_{q=1}^{Q} \sum_{n=1}^{N} X_{nh} \left| Y_{nq} - W_{hq} \right|}{\sum_{n=1}^{N} X_{nh}}, 1 \le h \le H \tag{26}$$

The objective function f_3, referred to as the learning resource cost goal, captures the cost related information associated with learning resources. This function is detailed in equation (27) and helps in managing the expenditure linked to various learning resources.

$$f_3 = \sum_{j=1}^{N} \sum_{i=1}^{N} x_{ar_i br_j} s_{ar_i br_j} \tag{27}$$

The objective function f_4, named the learning time management goal, calculates the gap between the time needed to complete learning resources and the time frame learners are willing to commit. This helps in aligning the learning process with the learner's available time, as detailed in equation (28).

$$f_4 = \begin{cases} \sum_{n=1}^{N} T_n X_{nh} - T_{lhn} > 0 \\ \sum_{n=1}^{N} T_n X_{nh} - T_{lhn} < 0 \end{cases}, 1 < h < H \tag{28}$$

The four sub functions above reflect the feature parameters of learners and learning resources. They jointly form a personalised learning path generation model. Lower values of the four objective functions indicate a better match between the generated path and learner requirements. The overall optimisation function integrates learners and learning paths via weighted sub mapping functions and is given by equation (29). This function represents the personalised learning path optimisation problem, with w_i denoting the weighting coefficients.

$$\min F(x) = \sum_{i=1}^{4} w_i f_i \tag{29}$$

3.2 Model framework

With the continuous advancement of the educational informatisation process, the demand for personalised learning is increasingly prominent. Although online learning platforms provide students with a vast amount of learning resources, they also make learners prone to losing their way when facing a huge amount of information, making it difficult for them to form an efficient learning path. The traditional methods for optimising learning paths have obvious limitations, such as ignoring the logical connections, semantic similarities among knowledge points and the individualised weak knowledge points of learners, resulting in the optimised learning paths lacking coherence and pertinence. To overcome these difficulties, this paper innovatively proposes a personalised learning path dynamic optimisation method integrating knowledge graphs, dedicated to constructing precise and dynamic learning paths to significantly improve learning efficiency and effectiveness.

The model design framework proposed in this paper is shown in Figure 1. To obtain the knowledge graph from raw data, the system follows a bottom-up pipeline: it first extracts SPO triples via automated knowledge extraction and fusion from heterogeneous learning-resource corpora, then incrementally constructs the ontology layer atop this data layer. Firstly, the DKT model is employed to conduct an in-depth analysis of the interaction behaviour sequence of learners on each knowledge point, accurately diagnosing the learners' mastery of the knowledge points. By constructing a multi-dimensional learner profile that includes the learners' knowledge status, the weak knowledge points of the learners are accurately identified. These mastery scores from the DKT model are then used to re-weight both the sequential links and semantic similarities encoded in the knowledge graph, so that the graph's edges reflect not only domain logic but also each learner's current deficits. Then, based on the knowledge graph, the sequential relationship and semantic similarity relationship between knowledge points are deeply mined to construct a knowledge graph enhancement model that comprehensively considers the logical sequence and semantic similarity of knowledge points, providing a knowledge logic basis for the construction of the learning path. The method integrates the PSO algorithm with the weak knowledge point data from learner profiles. The PSO fitness function explicitly incorporates these learner-weighted knowledge-graph constraints – mastery level, semantic proximity, and prerequisite order – so that every candidate path is evaluated against the learner's individual profile as well as the underlying knowledge structure. Using knowledge point mastery, semantic similarity, and sequence as constraints, it designs an effective fitness function. Through the swarm intelligence of the particle swarm, this approach dynamically optimises the sequence of learning path nodes. The PSO algorithm constantly adjusts the path sequence during the search process to find the optimal learning path, ensuring that learners can study in a reasonable knowledge order. The optimised path is retained as a living particle in MABPSO and is continuously re-evaluated as fresh learner-interaction data stream in; the fitness function is updated on the fly with the latest mastery estimates and newly identified weak points, enabling seamless, real-time path adjustment without restarting the optimisation cycle. At the same time, it takes into account the individualised weak knowledge points of learners, achieving the purpose of filling in the gaps and improving the learning efficiency.

Therefore, the dynamic optimisation method of personalised learning paths integrating knowledge graphs proposed in this paper effectively integrates the cognitive state of learners and the inherent logic of knowledge, and uses swarm intelligence algorithms to achieve precise optimisation of learning paths, providing a new solution for personalised learning. This method precisely locates weak knowledge points by constructing multi-dimensional learner portraits, and combines the logical and semantic associations of knowledge points mined from the knowledge graph to form an optimisation basis. On this basis, the PSO algorithm dynamically adjusts the order of path nodes to generate the optimal learning path. This framework not only fully considers the individualised needs of learners and the inherent logic of knowledge, but also ensures the real-time and adaptability of the learning path through a dynamic optimisation mechanism, providing an innovative solution for the field of personalised learning and effectively promoting the development of educational informatisation. In practice, the method is readily deployed on online platforms that continuously collect click-stream data and maintain scalable knowledge graphs; however, its effectiveness diminishes in offline or low-resource contexts where high-quality learner logs and dense graph embeddings are unavailable.

4 Experimental results and analyses

To evaluate the optimisation capability of the proposed MABPSO algorithm, it was tested on three unimodal functions (sphere, step, Rosenbrock) and three complex multimodal functions (Rastrigin, Ackley, Griewank). Comparative algorithms included BPSO with linearly decreasing w, UPBPSO with linearly increasing w, and the proposed MBPSO with an unknown – space – exploration mutation operator. In learning-path tasks, BPSO's simplicity risks premature convergence; MBPSO alleviates this with a mutation operator but retains linear weights, whereas MABPSO's nonlinear inertia and mutation jointly balance exploration and exploitation, delivering superior accuracy and stability at scale. Parameter values were anchored to established empirical baselines and then refined through systematic validation on a pilot learner cohort, ensuring the settings translate robustly from benchmark functions to live educational data. Each algorithm ran 30 times independently for each function in 300 – dimensional space, yielding 30 optimal solutions per function. The average, best, worst values and standard deviations of these solutions were recorded. Results are presented in Table 1.

Unimodal functions, with their single global optimum and absence of local optima, provide an excellent test bed for evaluating the convergence precision of optimisation algorithms. Examining Table 1, it is evident that, across the unimodal functions F1, F2, and F6, the MBPSO algorithm consistently delivers superior performance compared to BPSO and UPBPSO. For details, see Figure 2. This is reflected in its achieving lower best, worst, and mean values, which underscores its heightened convergence accuracy. Furthermore, the MABPSO algorithm eclipses MBPSO in these same metrics, positioning it as the most accurate among the four algorithms tested. When the focus shifts to multimodal functions, which are characterised by numerous local optima that escalate exponentially with increasing problem dimensions, the algorithms' capabilities to evade these local optima come under scrutiny. Within the context of multimodal functions F3, F4, and F5, MBPSO once again demonstrates its supremacy over BPSO and UPBPSO. However, it is MABPSO that secures the top spot across all algorithms, attaining the most favourable outcomes. The MBPSO algorithm owes its enhanced exploration prowess and local optimum avoidance capability in large part to the implementation of a mutation operator. Meanwhile, MABPSO's adoption of nonlinear inertia weight growth enables a more advantageous equilibrium between global exploration and local exploitation. This refinement not only amplifies the algorithm's convergence efficiency but also ensures that it can navigate complex optimisation landscapes with greater agility. Zooming in on the standard deviation metric, MABPSO stands out as the most stable performer on F1, F2, and F5. Even on F3, F4, and F6, where its standard deviation is marginally higher than that of BPSO and MBPSO, the disparity is negligible. This pattern of results strongly suggests that the MABPSO algorithm succeeds in enhancing both convergence accuracy and the capacity to break free from local optima, all the while preserving the algorithm's overall stability.

Table 1 Data when the test function is 300 dimensions

Function	*Algorithm*	*Best*	*Worst*	*Mean*	*Standard*
F1	BPSO	6.1E+01	7.6E+01	6.94+01	3.15E+00
	UPBPSO	5E+01	6.3E+01	5.80E+01	2.79E+00
	MBPSO	1.4E+01	2.3E+01	1.92E+01	2.04E+00
	MABPSO	*1.1E+01*	*1.4E+01*	*1.26E+01*	*9.64E-01*
F2	BPSO	2.01E+02	2.23E+02	2.13E+02	5.34E+00
	UPBPSO	1.79E+02	2.01E+02	1.89E+02	5.16E+00
	MBPSO	1.07E+02	1.21E+02	1.14E+02	3.77E+00
	MABPSO	*9.3E+01*	*1.03E+02*	*9.84E+01*	*2.63E+00*
F3	BPSO	1.75E+00	1.90E+00	1.83E+00	*3.36E-02*
	UPBPSO	1.61E+00	1.76E+00	1.68E+00	4.19E-02
	MBPSO	8.75E-01	1.1E+00	9.95E-01	4.88E-02
	MABPSO	*7.51E-01*	*8.75E-01*	*8.03E-01*	3.40E-02
F4	BPSO	8.97E+05	8.97E+05	8.97E+05	3.31E+00
	UPBPSO	8.97E+05	8.97E+05	8.97E+05	3.48E+00
	MBPSO	8.97E+05	8.97E+05	8.97E+05	*1.45E+00*
	MABPSO	*8.97E+05*	*8.97E+05*	*8.97E+05*	1.46E+00
F5	BPSO	2.80E-01	3.29E-01	3.01E-01	1.26E-02
	UPBPSO	2.32E-01	2.74E-01	2.56E-01	9.73E-03
	MBPSO	7.34E-02	1.05E-01	8.79E-02	7.39E-03
	MABPSO	*4.37E-02*	*6.42E-02*	*5.39E-02*	*5.84E-03*
F6	BPSO	8.85E+03	1.01E+04	9.58E+03	3.09E+02
	UPBPSO	8.15E+03	9.45E+03	8.96E+03	3.45E+02
	MBPSO	3.22E+03	4.33E+03	3.73E+03	*2.76E+02*
	MABPSO	*2.01E+03*	*3.37E+03*	*2.52E+03*	3.66E+02

Figure 1 A dynamic optimisation model framework for personalised learning paths integrating knowledge graphs (see online version for colours)

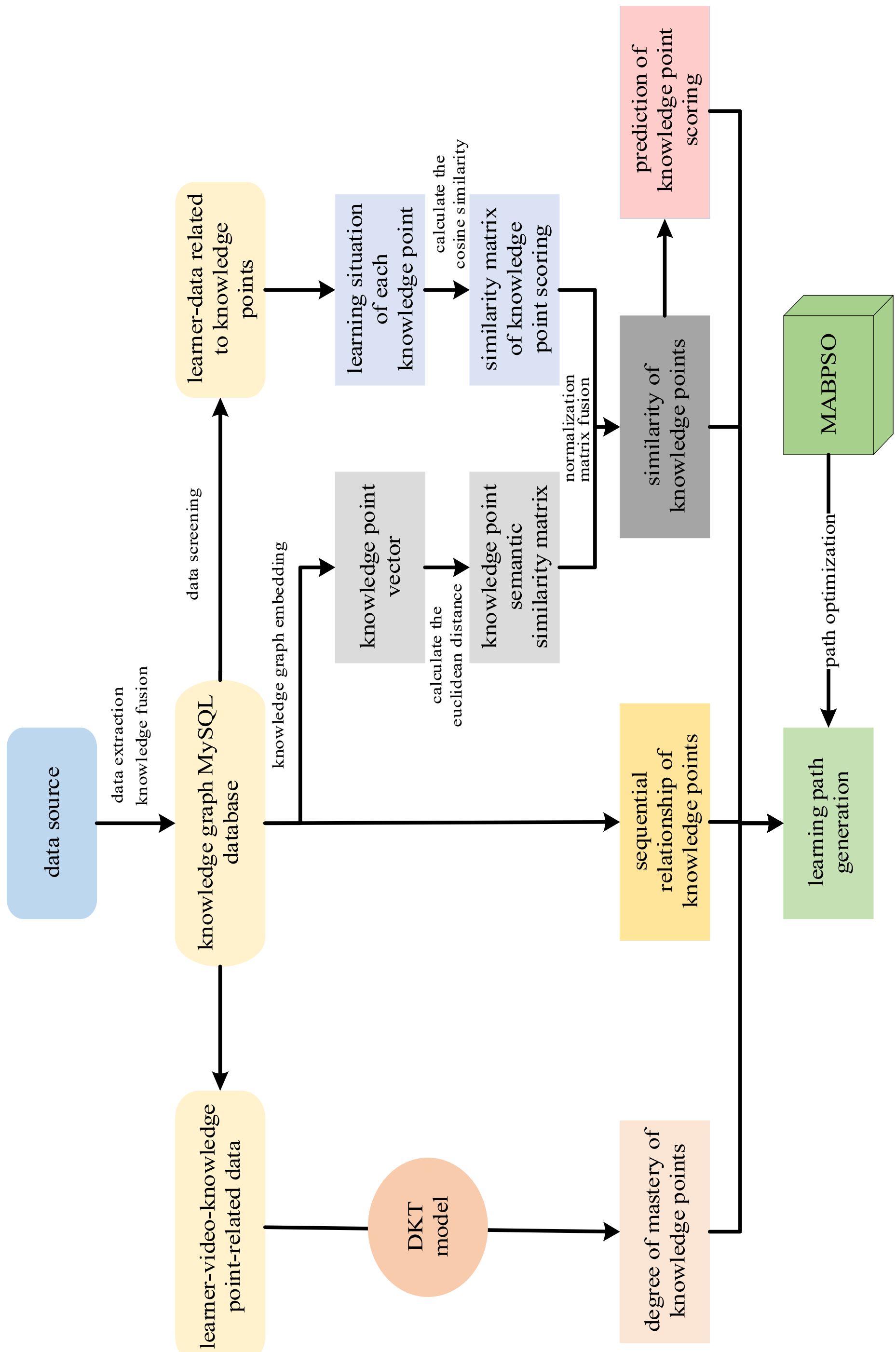
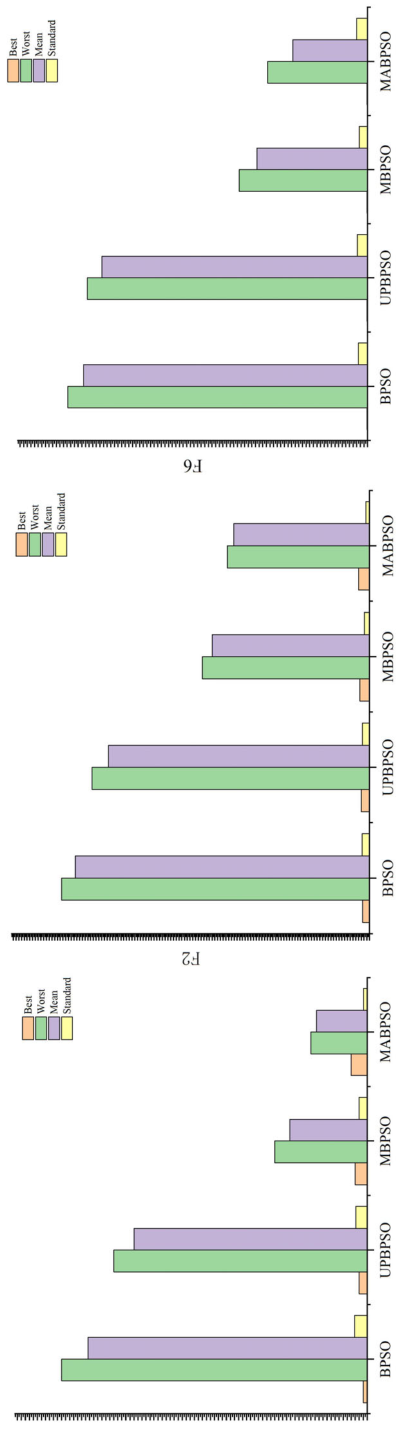


Figure 2 Comparison chart of unimodal functions (see online version for colours)



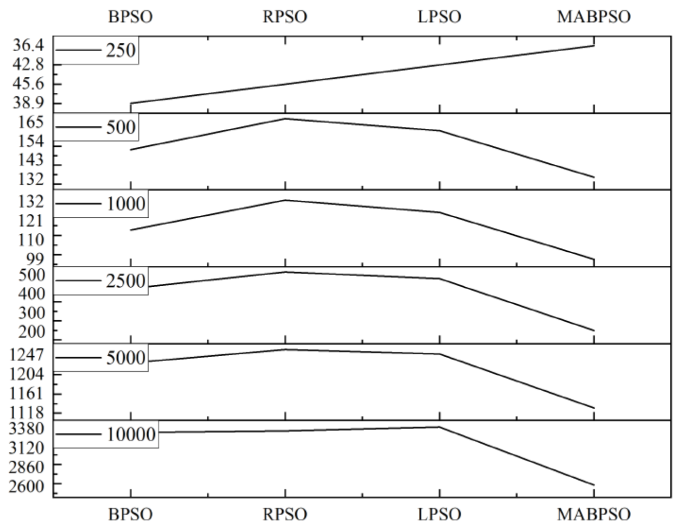
The personalised learning path model serves as the foundation for optimisation using four algorithms: the basic BPSO, RPSO, LPSO, and the proposed MABPSO. To evaluate these methods, six differently scaled personalised learning path optimisation problems were established, with performance assessed via mean and variance. The optimisation effect is influenced by varying numbers of learners, learning resources, and knowledge points, prompting experiments of different scales. The problem scale is determined by multiplying the number of knowledge points, learning resources, and learners. Experiments one to six have dimensional sizes of 250, 500, 1,000, 2,500, 5,000, and 10,000 dimensions respectively. Each core algorithm's data was obtained through 30 independent runs on the MATLAB platform, with a maximum of 100 iterations per run. Table 2 presents the mean and variance from 30 runs of the four algorithms, with optimal values in bold.

Table 2 Comparison of performance indicators of different personalised learning path optimisation methods

Dimension	*Evaluation*	*BPSO*	*RPSO*	*LPSO*	*MABPSO*
250	avg	3.89E+01	4.56E+01	4.28E+01	*3.64E+01*
	var	6.38E-01	1.83E-01	1.19E+00	*1.40E-01*
500	avg	1.52E+02	1.70E+02	1.63E+02	*1.36E+02*
	var	3.14E+00	*1.28E+00*	4.99E+00	3.41E+00
1,000	avg	1.13E+02	1.30E+02	1.23E+02	*9.64E+01*
	var	2.01E+00	*1.13E+00*	4.36E+00	1.49E+00
2,500	avg	4.71E+02	5.58E+02	5.22E+02	*2.49E+02*
	var	6.89E+01	*2.20E+01*	8.33E+01	4.09E+01
5,000	avg	1.23E+03	1.26E+03	1.25E+03	*1.13E+03*
	var	1.29E+01	2.72E+00	1.25E+01	1.65E+01
10,000	avg	3.29E+03	3.31E+03	3.36E+03	*2.58E+03*
	var	1.02E+02	*3.40E+01*	1.41E+02	3.84E+02

The comprehensive optimisation function $F(x)$ signifies how well a learning path aligns with learner characteristics. Lower $F(x)$ values indicate better alignment with learner needs and higher learning quality, whereas higher values suggest a poor fit. Table 2 presents the average and variance of $F(x)$ for the learning paths generated in this study. Experiments one, two, and three vary only in the number of knowledge points. Comparing these three experiments in Table 2 reveals that as the number of knowledge points grows, the MABPSO algorithm demonstrates superior convergence accuracy. Although it shows the best variance only in experiment one, the differences in variance across the other experiments are minimal, indicating that the MABPSO algorithm maintains acceptable stability. Similarly, experiments two, four, five, and six differ primarily in the number of learners. Observing these experiments in Table 2 shows that as the number of learners increases, the MABPSO algorithm continues to exhibit the highest convergence accuracy. While its variance is not the best, it remains comparable to other algorithms, further confirming the acceptable stability of the MABPSO algorithm. Overall, the MABPSO algorithm proves to be both efficient and reliable in generating learning paths that meet learner needs.

Figure 3 Algorithm comparison chart



As observed in Figure 3, across the six experiments, the MABPSO algorithm exhibits superior convergence accuracy compared to other algorithms. This suggests that learning paths optimised by MABPSO align more closely with learner needs. The algorithm's performance indicates it can effectively enhance learning quality by fine tuning paths to better suit individual requirements. MABPSO's ability to achieve high precision convergence makes it a reliable choice for personalised learning path optimisation, offering a significant improvement over other methods in meeting diverse learning demands.

To ensure the validity of these findings, the experimental design reproduces six real-world problem scales, benchmarks four algorithms on standard uni-and multimodal test functions, and employs 30 independent runs with statistical metrics, thereby guaranteeing both representativeness and robustness. In summary, empirical results on personalised learning-path tasks show that the MABPSO optimised sequences cut average learning time, reduce error rates, and increase mastery scores compared with baseline paths, confirming that the dynamic adjustment mechanism directly translates algorithmic superiority into measurable gains in learner efficiency.

5 Conclusions

To address learners' 'information overload' and 'learning disorientation' in online settings, this paper innovatively proposes a dynamic personalised learning path optimisation method integrating knowledge graphs. The method first leverages the DKT model to deeply analyse learners' interaction behaviour sequences on knowledge points, building a multi dimensional learner profile that includes knowledge status and accurately identifying weak knowledge points. Subsequently, based on knowledge graphs, it delves into the sequential and semantic similarity relationships of knowledge points, constructing a knowledge graph enhancement model that establishes the knowledge logic foundation for learning path optimisation. Finally, the PSO algorithm is introduced. With the mastery degree of knowledge points, semantic similarity and sequential relationship as constraint conditions, the fitness function is carefully designed. Swarm intelligence is utilised to dynamically adjust the order of learning path nodes and tailor the optimal learning path for learners. This series of processes fully integrates the individualised needs of learners with the inherent logic of knowledge. With the powerful optimisation capabilities of swarm intelligence algorithms, it achieves precise and dynamic optimisation of the learning path, effectively enhancing the knowledge mastery effect and learning efficiency of learners, injecting new vitality into the field of personalised learning, and powerfully promoting the development of educational informatisation.

Declarations

All authors declare that they have no conflicts of interest.

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