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PAPER

Machine Learning-Based Personalized Learning Path Decision-Making Method on Intelligent Education Platforms

Yan Zhang(✉)

Department of Artificial Intelligence, Hebi Polytechnic, Hebi, China

zly570725@163.com

ABSTRACT

With the rapid development of information technology, the application of intelligent education platforms has become increasingly widespread. Traditional teaching methods struggle to meet the demands for personalized learning. Personalized learning path decision-making methods, which analyze learners' behavioral data and mastery of knowledge points, tailor learning paths for each individual. Current research indicates that these methods can significantly improve learning efficiency and effectiveness. However, existing personalized learning path decision-making methods still have shortcomings in predicting the difficulty of knowledge points and dynamically adjusting path recommendations. This paper proposes a machine learning-based personalized learning path decision-making method, focusing on two main aspects: predicting the difficulty of knowledge points for personalized learning and integrating knowledge point localization for personalized learning path decisions. Through accurate prediction of knowledge point difficulty and dynamically optimized learning path recommendations, this method provides more refined and personalized learning support on intelligent education platforms, aiming to enhance learners' learning experience and outcomes.

KEYWORDS

intelligent education platform, machine learning, personalized learning, learning path decision-making, knowledge point difficulty prediction, dynamic optimization

1 INTRODUCTION

In the field of modern education, with the rapid development of information technology, the application of intelligent education platforms is becoming increasingly widespread [1–3]. Traditional teaching methods can no longer meet the needs for personalized learning, as learners require more customized learning paths to improve learning efficiency and effectiveness [4, 5]. Currently, machine

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learning-based personalized learning path decision-making methods are gradually becoming a research hotspot. By analyzing learners' behavioral data and knowledge point mastery, these methods tailor learning paths for each learner to help them better master knowledge.

The research significance of personalized learning path decision-making lies in its ability to significantly enhance learning efficiency and effectiveness [6–9]. Through precise knowledge point localization and learning path recommendation, learners can study at a difficulty and pace suitable for them, thus avoiding the drawbacks of the "one-size-fits-all" approach in traditional teaching [5, 10–12]. More importantly, personalized learning paths can stimulate learners' interest and motivation, making the learning process more proactive and efficient. This has an important driving effect on the development of education platforms and the improvement of education quality.

However, existing personalized learning path decision-making methods still have some shortcomings. Many methods lack accuracy in predicting the difficulty of knowledge points and cannot accurately assess learners' mastery of different knowledge points [13, 14]. Additionally, existing methods also lack a dynamic adjustment mechanism for learning path recommendations and cannot respond in real-time to changes in learners' learning status and needs [15, 16]. Traditional methods mostly rely on static data and rules, making it difficult to meet the needs for personalized and refined learning.

To address the above issues, this paper proposes a machine learning-based personalized learning path decision-making method for intelligent education platforms. The main content of the research includes two parts: first, predicting the difficulty of knowledge points for personalized learning, accurately assessing the difficulty of each knowledge point through machine learning algorithms; and second, integrating knowledge point localization for personalized learning path decision-making, dynamically adjusting the learning path based on learners' mastery of knowledge points. This method not only improves the accuracy of knowledge point difficulty prediction but also achieves dynamic optimization of learning paths, providing strong technical support and a theoretical foundation for intelligent education platforms. Through this research, we hope to promote the development of personalized education and enhance learners' learning experiences and outcomes.

2 PREDICTION OF KNOWLEDGE POINT DIFFICULTY FOR PERSONALIZED LEARNING

2.1 Calculation of knowledge point difficulty coefficient

The application of knowledge graphs in the field of education can provide personalized learning paths for learners based on the relationships and hierarchical structures between knowledge points. Specifically, when a learner encounters difficulties in learning a certain knowledge point, such as integration techniques in calculus, the system can find the parent nodes of the knowledge point through its position in the graph and infer the prerequisite knowledge that the learner needs to master due to the hierarchical and associative characteristics of the knowledge graph. For example, before learning integration techniques, learners may need to understand the basic concepts of calculus and related knowledge of derivatives. Through this process, the system can automatically identify and recommend prerequisite knowledge points suitable for the learner's current knowledge level. In addition, the knowledge graph can help learners consolidate related knowledge by recommending knowledge points at the same level. If a certain knowledge point is relatively simple for a learner, the system can use depth-first traversal or related algorithms to recommend other knowledge points at the same level, helping learners expand their knowledge base. This knowledge graph-based localization method not only focuses on the learner's current needs but also forms a dynamic and personalized learning path through multi-level and multi-angle knowledge associations. Figure 1 shows the personalized learning path decision-making approach proposed in this paper for intelligent education platforms.

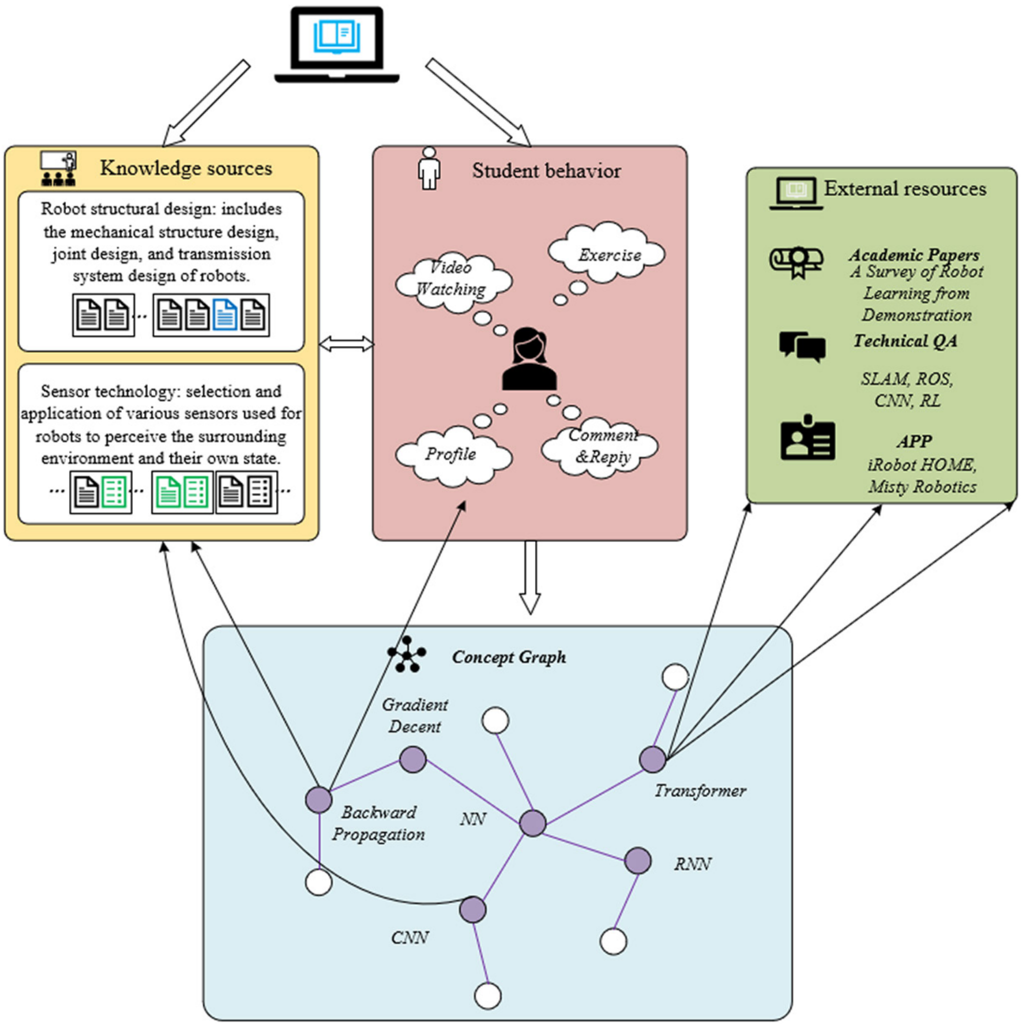

Fig. 1. Personalized learning path decision-making approach for intelligent education platforms

The key issue in realizing the aforementioned knowledge point localization based on the knowledge graph is to accurately predict the difficulty level of the target knowledge point for the learner. For an intelligent education platform, predicting the difficulty level of the target knowledge point for personalized learning is a complex and critical problem. To achieve this goal, it is necessary to comprehensively analyze various behavioral data of learners on the platform, especially behaviors related to video learning resources. The core of this process is to infer their mastery of the target knowledge point and the learning difficulty by analyzing behavioral features such as learning frequency, cumulative learning duration, and the number of pauses and drags in the video.

On the intelligent education platform, the prediction method of the difficulty level of the target knowledge point for personalized learning learners mainly includes the fusion analysis of learning behaviors. Specifically, this method achieves precise prediction of the difficulty level of knowledge points through the following three steps:

1. Analyzing the learning frequency of learners for the same knowledge point resources. Learning frequency refers to the number of times a learner repeatedly watches the same knowledge point video within a certain period. The higher the frequency, the higher the difficulty of the knowledge point for the learner, as the learner needs to watch it multiple times to understand and master the knowledge point. Therefore, by counting the learning frequency of learners, the difficulty level of the knowledge point can be preliminarily judged. Suppose the learner is denoted by j, and the target knowledge point is denoted by i. The set of all knowledge points is denoted by J. The learning frequency of learner i for the knowledge point u resource is denoted by $FR(i, j)$, and the quantification formula of this feature is given by the following formula:

$$f_d(i, j) = \frac{FR(i, j)}{\underset{1 \le j \le J}{MAX}\, FR(i, j)} \tag{1}$$

2. Calculating the learning duration of learners for knowledge point resources. Specifically, by comparing the actual learning duration of learners with the total duration of the video resources, a learning duration ratio is obtained. If the actual learning duration of the learner is longer than the video duration, it indicates that the learner spent extra time understanding and digesting the knowledge point, suggesting that the knowledge point is more difficult for the learner. To quantify this feature, its weight will not exceed 1, ensuring its weight is within a reasonable range regardless of the length of the learning duration. Suppose the learning duration of learner i for the knowledge point j resource is denoted by $S(i, j)$, and the original duration is denoted by S, then the weight calculation formula is:

$$f_s(i, j) = \begin{cases} \dfrac{S(i, j)}{3 * S}, \dfrac{S(i, j)}{S} \le 3 \\ 1, \dfrac{S(i, j)}{S} > 3 \end{cases} \tag{2}$$

3. Analyzing the number of pauses and drags of learners for knowledge point resources. Frequent pauses and drags usually indicate that learners encounter confusion in certain key parts and need to watch repeatedly to understand the content. By calculating the ratio of the number of pauses and drags of learners to a preset maximum number, the degree of confusion of learners on the knowledge point can be derived. This ratio will also not exceed 1, ensuring its rationality and comparability in the analysis. Suppose the number of drags for learner j's knowledge point video resource is denoted by $PA(i, j)$, and the number of drags is denoted by DR. The quantification formula for this feature is given by the following formula:

$$f_{o,f}(i,j) = \frac{PA(i,j) + DR(i,j)}{\underset{1 \le j \le J}{MAX}(PA(i,j) + DR(i,u))} \tag{3}$$

By integrating these three steps, the intelligent education platform can weight and fuse the learning frequency, learning duration ratio, and pause and drag ratio to form a comprehensive index to predict the difficulty of the target knowledge point for the learner.

$$o(i,u) = \beta * f_d(i,j) + \alpha * f_s(i,j) + \varepsilon * f_{of}(i,j) \tag{4}$$

Literature has tested 67 different combinations (α, β, γ) and ($\beta, \alpha, \varepsilon$) under integer ratios. For example, learners $u1i1$ and $u2i2$ have both studied knowledge point $k1j1$, with no interaction with other resources; $u1i1$ interacts more with learner $u3i3$, but the difficulties are different.

To accurately calculate the difficulty of the target knowledge point, this paper constructs a learner-knowledge point difficulty matrix, where each element of the matrix reflects the difficulty level of a specific learner on a particular knowledge point. This matrix can be calculated comprehensively through multiple dimensions such as learning frequency, learning duration ratio, pause, and drag times. Furthermore, based on this matrix, this paper applies the collaborative filtering algorithm to calculate the similarity between learners. Traditional collaborative filtering algorithms, such as user-user collaborative filtering or item-based collaborative filtering, face the problem of data sparsity. To address this issue, this paper introduces a weighted similarity calculation method, combining more contextual information such as the learner's background knowledge level, learning path, and the association of knowledge points before and after, thus improving the accuracy of similarity calculation.

2.2 Prediction of target knowledge point difficulty

To accurately predict the difficulty of target knowledge points and optimize the learning experience, this paper proposes a user similarity calculation method based on knowledge point difficulty for personalized learning. To calculate user similarity, two main factors need to be considered: the differences between learners and the fusion calculation of unrelated learners.

1. Differences between learners: Since different learners have different levels of reception for the same knowledge point, a similarity calculation needs to quantify this difference. Specifically, it calculates the absolute value of the difference in difficulty coefficients for the same knowledge point between learners, i.e., $|o(i1, j1) – o(i2, j1)|$. The smaller this absolute value, the smaller the difference in understanding of the same knowledge point between the two learners. This value is used as an indicator for similarity calculations. Considering the cognitive level differences between learners, it is necessary to average the coefficients of knowledge points with excessive differences and finally use the form of the maximum difference average ratio to represent the differentiation degree of two learners on the same knowledge point. Suppose the set of knowledge points that learner i and n have studied together is represented by Z, the average difficulty coefficients of learners i and n for the commonly studied knowledge points

are represented by $\overline{o(i,j)}$ and $\overline{o(n,j)}$, the maximum difficulty coefficient in the learner-knowledge point difficulty matrix is represented by *fMAX*, and the minimum difficulty coefficient is represented by *fMIN*. The calculation formula is:

$$f_f(i,n) = 1 - \frac{\sqrt{\sum_{j=1}^{Z} \left\| o(i,j) - o(n,j) \right\| * \left| \overline{o(i,j)} - \overline{o(n,j)} \right|}}{fMAX - fMIN} \tag{5}$$

2. Fusion calculation of unrelated learners: Due to the data sparsity problem, bias may occur in similarity calculations. Therefore, when calculating learner similarity, it is necessary to consider the similarity between learners who have not studied the same knowledge point together. To do this, some methods can be introduced, such as filling in missing data, using matrix decomposition techniques, or supplementing this information by combining content features such as learners' learning paths and learning time, ensuring the comprehensiveness and accuracy of similarity calculations. Suppose the predicted difficulty coefficient of learner i for the target knowledge point j is represented by $o'(i, j)$, and the average difficulty coefficient of learner i for the set of knowledge points t that have been studied is represented by $\overline{o(i,t)}$. The influence rate calculation formula is as follows:

$$\phi = \frac{Z}{\left|J_i\right| * \left|J_n\right|} \tag{6}$$

Combining the above two formulas can further calculate the similarity of learners:

$$SIM(i,n) = \varphi * f_f(i,n) \tag{7}$$

Based on the similarity calculation results, the difficulty of the target knowledge point can be predicted, and the prediction formula is given by the following equation:

$$o'(i,j) = \overline{o(i,t)} + \frac{\sum_{n=1}^{v} \left(o(n,j) - \overline{o(n,t)} \right) * SIM(i,n)}{\sum_{n=1}^{v} SIM(i,n)} \tag{8}$$

3 INTEGRATION OF KNOWLEDGE POINT LOCALIZATION FOR PERSONALIZED LEARNING PATH DECISION-MAKING

3.1 Embedding knowledge point relevance factors

On an intelligent education platform, there are inherent logical relationships and dependencies between knowledge points. After mastering a certain knowledge point, learners naturally need to learn subsequent related knowledge points to form a systematic knowledge framework. Secondly, learners' cognitive load and learning interests influence the selection of knowledge points. When learners make good progress on certain knowledge points, they usually develop an interest and motivation to continue learning similar knowledge points. This learning motivation not only helps consolidate the knowledge already mastered but also stimulates learners' desire to explore new knowledge. In addition, the progressive difficulty of knowledge points is another factor that needs consideration. Learners can only challenge more difficult knowledge points after gradually mastering the basic ones. Figure 2 shows the personalized learning path decision-making framework integrating knowledge point localization.

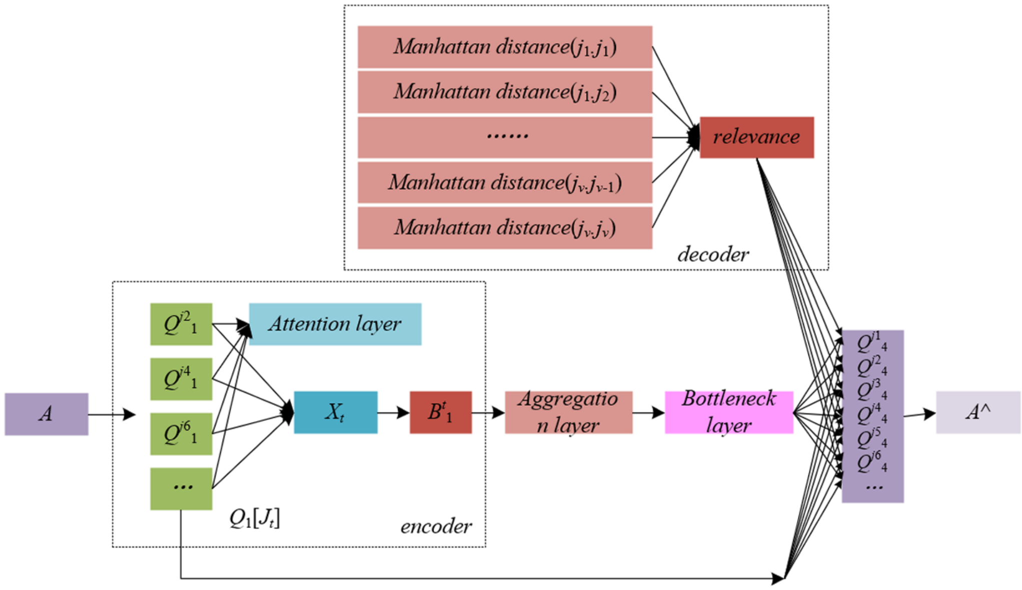

Fig. 2. Personalized learning path decision-making model framework integrating knowledge point localization

Considering the above factors comprehensively, this paper proposes a model based on SaeCrdRec to discover the influence of learned knowledge points on unlearned knowledge points. By analyzing learners' knowledge point learning history, this model identifies these inherent logical relationships and can effectively predict the knowledge points that learner should learn next, thus recommending unlearned knowledge points closely related to the learned ones. This model can also identify the knowledge points in which learners are more interested and confident by analyzing their performance on different knowledge points, thereby recommending appropriate knowledge points in the personalized learning path decision-making process to meet learners' learning needs and motivations. Specifically, assume that the set of knowledge points included in the learner's registered course is represented by $J_t = \{j_1, \ldots, j_v\}$, let $M_t \in R^{V \times v}$, and $Q_4 \in R^{V \times G}$, then the influence factor of learned knowledge points on unlearned knowledge points is:

$$M_t = Q_4 \cdot Q_1[K_t] \tag{9}$$

There are natural precursor and subsequent relationships between knowledge points, and some knowledge points are the foundation for subsequent ones. For example, learners need to master basic algebra knowledge before understanding specific applications in calculus. This hierarchical relationship determines the rationality and coherence of the learning path and must be considered in personalized learning path decision-making. Considering the hierarchical relationships between knowledge points helps systematically build learners' knowledge frameworks, preventing the fragmentation of knowledge structures and ensuring that learners can solidly master each knowledge point. Considering this hierarchical relationship can reduce learners' cognitive load and help them learn in a progressive manner, thereby improving learning efficiency and effectiveness. Therefore, this paper proposes the idea of integrating the course relevance decoder and applies it to the integration of knowledge point hierarchical relationships. Specifically, the relevance between knowledge points can be obtained through the information mining of knowledge point description texts. Using natural language processing techniques, the description texts of knowledge points are analyzed to extract key features to construct the relevance matrix between knowledge points. This matrix not only reflects the direct relevance of knowledge points but can also further capture implicit deep-level relationships through deep learning models. Assuming that the element product is represented by ⊗ and the influence of each knowledge point on other knowledge points is represented by each column in M_t, then this matrix can be represented as:

$$M_t = (Q_4 \cdot Q_1[J_t]) \otimes F[J_t] \tag{10}$$

To calculate the influence of all knowledge points on unlearned knowledge points, sum each row of M_t. Assuming the row and column index values in the M_t matrix are represented by u and k, then we have:

$$m_t = \sum_{u=1}^{V} \sum_{k=1}^{v} M_t^{(u,k)} \tag{11}$$

After comprehensively considering the embedded knowledge point relevance factors, the corresponding output vector $\hat{a}_t$ in the reconstruction space of the autoencoder can be obtained. Suppose the learner preference feature representation obtained by the self-attention mechanism encoder is represented by $Q_4 \cdot b_3^{\gamma}$, the course relevance calculated by the course relevance decoder is represented by m_t, and the offset value is represented by y_4. The calculation formula is:

$$\hat{a}_t = d_4(Q_4 \cdot b_3^{\gamma} + m_t + y_4) \tag{12}$$

3.2 Model training

Learners' preferences for different knowledge points change dynamically during the learning process. Traditional implicit feedback methods based on registered courses can only capture learners' preferences at a relatively coarse-grained level, while analysis at the knowledge point level can provide more fine-grained preference information. Moreover, learners' preferences for knowledge points not only influence their learning path choices but also reflect their interests and needs in certain fields. Understanding these preferences can help the system better recommend suitable learning content and avoid recommending irrelevant or repetitive knowledge points. Therefore, this paper introduces a learner knowledge point preference confidence matrix for personalized learning path decision-making. First, collect learners' learning behavior data on the platform, including the frequency of learning knowledge points, learning duration, completion status, etc. Represent learners' behavior data on the learned knowledge points as positive training examples that reflect the learners' real learning situation and preferences. Furthermore, treat the data on unlearned knowledge points uniformly as negative training examples. When constructing the confidence matrix, these negative examples need to be assigned the same initial weight value. As the learning frequency of certain knowledge points by learners increases, the corresponding weight values will also increase, showing a proportional trend, thereby dynamically reflecting the changes in learners' preferences for different knowledge points. Finally, based on these weight values, a confidence matrix Z that reflects learners' preferences for knowledge points can be constructed. Each element in matrix Z represents the learner's preference degree for a specific knowledge point, and by adjusting the weights of the matrix, learners' interests and needs can be more accurately captured. Suppose the confidence weight parameters are represented by β and γ, and when the learner's learning frequency is greater than 0, it is represented by $d_{t,z}$. The method for setting the element weights in the matrix is shown as follows:

$$Z_{t,z} = \begin{cases} 1 + \beta \log\left(1 + d_{t,z} / \gamma\right) \\ 1 \end{cases} \tag{13}$$

The objective function of the model embedded with the confidence matrix is given by the following equation:

$$LOSS = \sum_{t=1}^{L} \sum_{z=1}^{V} \left\| Z \otimes (A_{t,z} - \hat{A}_{t,z}) \right\|_2^2 \tag{14}$$

Suppose the regularization parameter is represented by η, and the learning parameters in the corresponding attention layer and merge layer are represented by Q_x and Q_s. To enable the model to achieve higher generalization performance while better mitigating noise data, the expression of the model objective function with the regularization term embedded is given by the following equation:

$$M = LOSS + \eta\left(\left\| Q_u \right\|_2^2 + \left\| Q_x \right\|_2^2 + \left\| Q_s \right\|_2^2 \right) \tag{15}$$

The model training method for the personalized learning path decision-making model integrating knowledge point localization proposed in this paper aims to provide more precise and effective learning path recommendations to meet the personalized needs of individual learners. The input of the model includes data sources from the intelligent education platform and course description text information. These data not only provide rich learning resources but also include learners' behavior data and detailed descriptions of the courses, enabling the recommendation system to more comprehensively understand the learners' needs and the content of the courses. To handle this large and complex data, this paper adopts a model architecture based on autoencoders. Autoencoders effectively extract important features from the data by compressing high-dimensional data into low-dimensional latent space and then reconstructing the input data from the latent space. During the model training process, the stochastic gradient descent method is adopted. This method has the advantages of reducing computational complexity and providing good parallelism, making it very suitable for handling large-scale data. Specifically, all parameters of the model are updated through the gradient descent method of back propagation to minimize the objective function. In this process, calculating the partial derivatives of all parameters is a key step, ensuring that the model can gradually approach the optimal solution, thereby improving the accuracy and effectiveness of the recommendations.

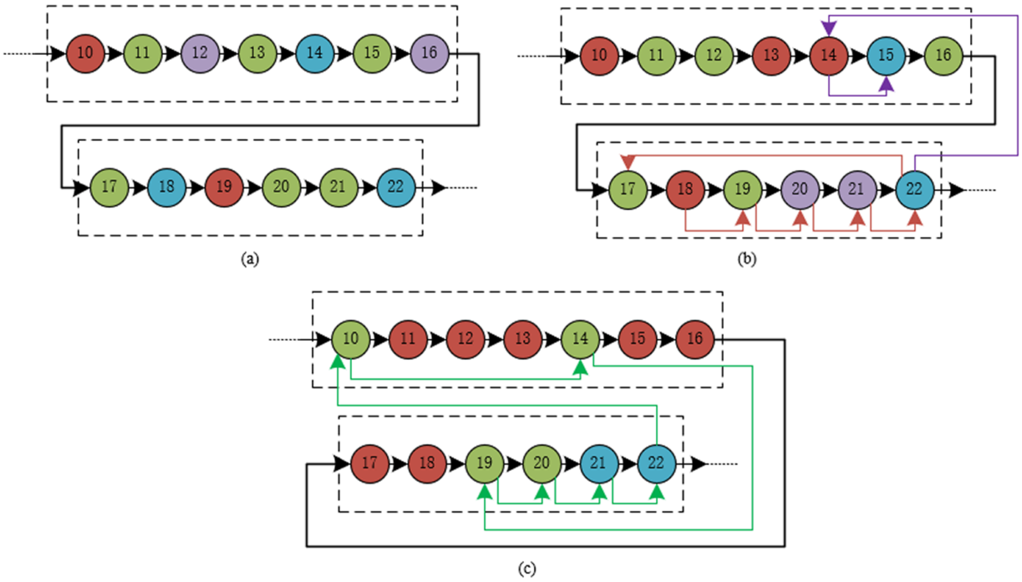

Fig. 3. Three typical personalized learning paths integrating knowledge point localization

In addition, to further optimize the efficiency and effectiveness of model training, this paper uses the Adam optimization method. The Adam optimization method can adaptively adjust the learning rate, providing more stable and faster convergence by combining the advantages of momentum and RMSProp optimization methods. This is particularly important in big data environments, as it can significantly reduce training time while improving the model's performance. Combined with personalized learning path decision-making integrating knowledge point localization, this model dynamically adjusts the learning path by analyzing learners' knowledge point mastery. Specifically, the model constructs a confidence matrix reflecting learners' knowledge levels based on their learning behavior data on different knowledge points. Then, based on this confidence matrix, the recommendation system can update the learning path in real-time, ensuring that learners receive enhanced learning on the knowledge points they are interested in and need to improve. Figure 3 shows three typical personalized learning paths that integrate knowledge point localization.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Comparison of effects of different decision models

Methods	Precision@5	Precision@10	Recall@5	Recall@10	F1-Score@5	F1-Score@10
Collaborative Filtering Algorithm	0.1204	0.1024	0.1005	0.1689	0.1089	0.1245
Neural Network Model	0.1658	0.1236	0.1423	0.2214	0.1524	0.1632
Graph Clustering Algorithm	0.1874	0.1425	0.1635	0.2563	0.1745	0.1856
The Proposed Model	0.2136	0.1632	0.2458	0.3526	0.1736	0.1987

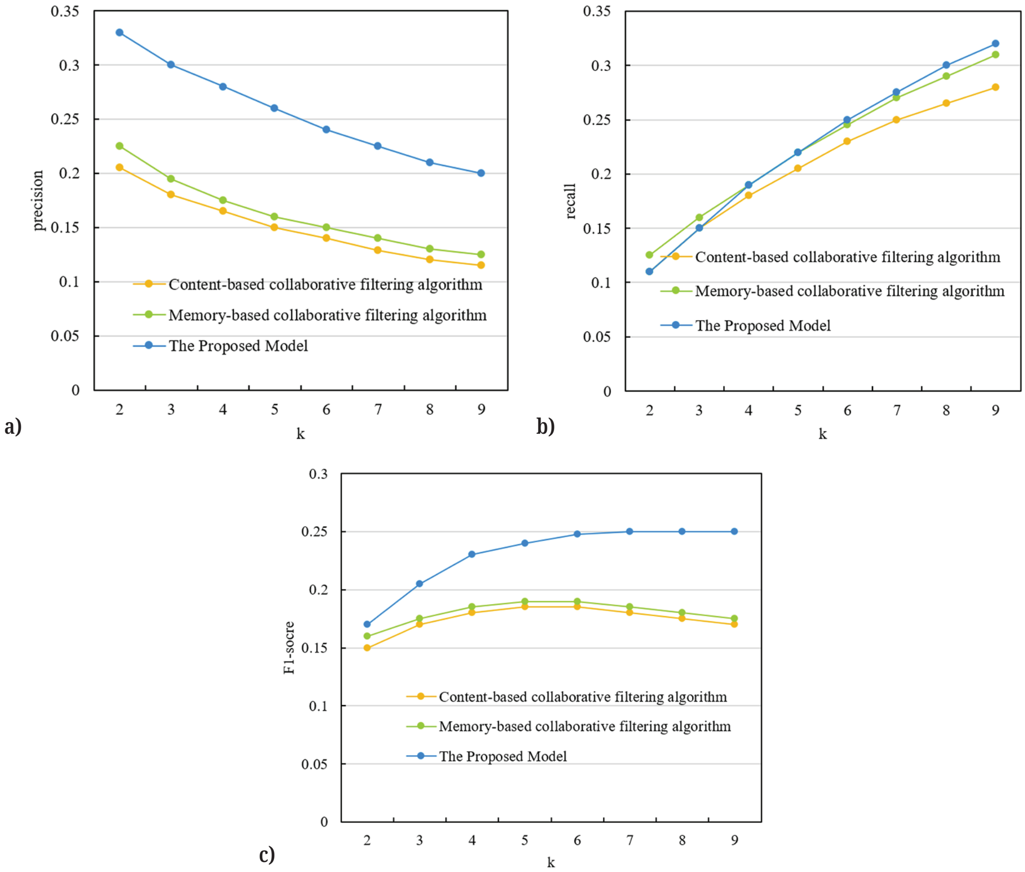

Fig. 4. Comparison results of decision performance between proposed model and collaborative filtering algorithm

From the comparison of the effects of different methods in Table 1, it's known that the different methods' performance on precision@5, precision@10, recall@5, recall@10, F1-score@5, and F1-score@10 varies. The collaborative filtering recommendation algorithm has precision at 5 and precision at 10 of 0.1204 and 0.1024, respectively, while the neural network model and graph clustering algorithm show improvements in these two indicators. Particularly, the proposed model achieves 0.2136 and 0.1632 in precision at 5 and precision at 10, respectively, significantly higher than other methods. In terms of recall at 5 and recall at 10, the proposed model also performs excellently, reaching 0.2458 and 0.3526, far exceeding the performance of other models. Additionally, the proposed model shows superior performance in F1-score at 5 and F1-score at 10, with values of 0.1736 and 0.1987, respectively. These data indicate that the proposed model outperforms existing collaborative filtering recommendation algorithms, neural network models, and graph clustering algorithms in all evaluation metrics. According to the above experimental results, the proposed machine learning-based personalized learning path decision-making method performs well in all indicators. The significant improvement in precision and recall metrics particularly demonstrates that the proposed model has higher accuracy and comprehensiveness in personalized learning path recommendation.

By comparing precision, recall, and F1 metrics, it's known that the proposed model significantly outperforms the content-based collaborative filtering algorithm and the memory-based collaborative filtering algorithm at multiple k-values (see Figure 4). In terms of precision, the proposed model performs excellently in the range of k-values from 2 to 9, with values of 0.33, 0.3, 0.28, 0.26, 0.24, 0.225, 0.21, and 0.2, respectively. Compared to the content-based and memory-based collaborative filtering algorithms, which have a maximum value of 0.225 in the same range, the improvement is significant. For recall, the values of the proposed model from k = 2 to k = 9 are 0.11, 0.15, 0.19, 0.22, 0.25, 0.275, 0.3, and 0.32, respectively. Although it is on par with other algorithms at k = 2, it shows a significant improvement at subsequent k values, reaching 0.32 at k = 9. In terms of F1 metrics, the proposed model also shows stable and superior performance, with values from k = 2 to k = 9, being 0.17, 0.205, 0.23, 0.24, 0.248, 0.25, 0.25, and 0.25, respectively. In contrast, other algorithms have values of only 0.17 and 0.175 at k = 9, highlighting the clear advantage of the proposed model. From the above experimental results, the proposed machine learning-based personalized learning path decision-making method shows significant advantages in precision, recall, and F1 metrics. Particularly in precision and F1 metrics, the proposed model consistently outperforms the content-based and memory-based collaborative filtering algorithms at various k-values, demonstrating its excellent performance in recommendation accuracy and overall performance.

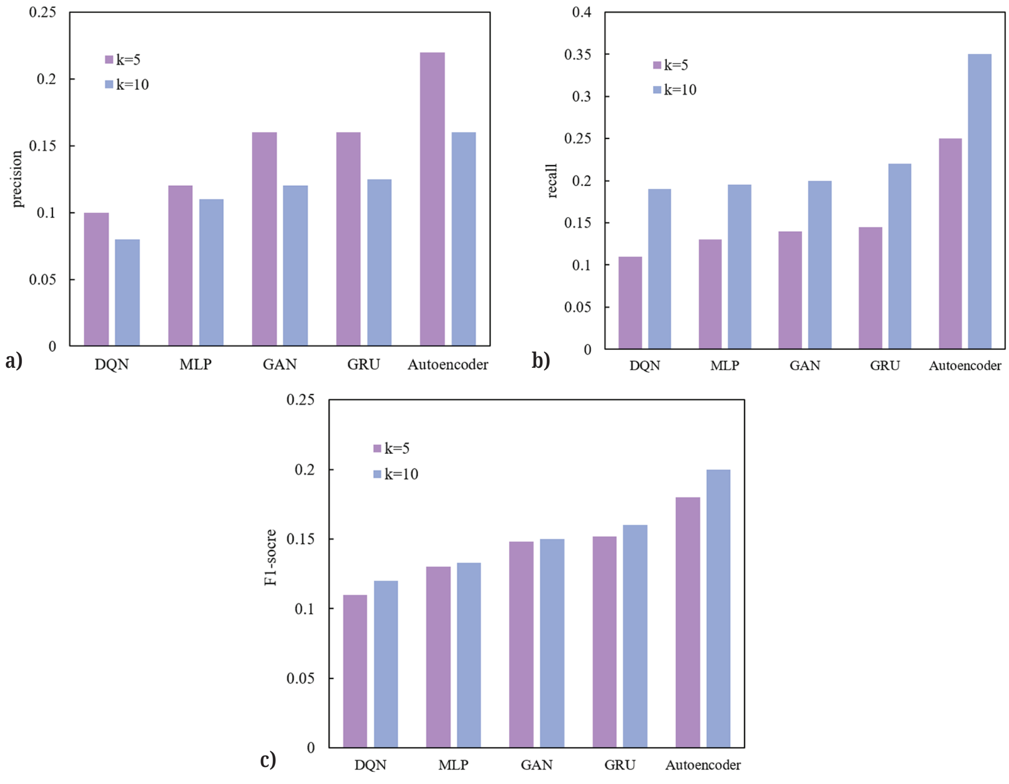

Fig. 5. Comparison results of decision performance between proposed model and neural network models

From the experimental results, the proposed personalized learning path decision-making method outperforms other neural network models in precision, recall, and F1 metrics (see Figure 5). In terms of precision, the proposed model achieves 0.22 and 0.16 at k = 5 and k = 10 respectively, significantly better than other models such as Deep Q-Network (DQN) (0.1 and 0.08), Multilayer Perceptron (MLP) (0.12 and 0.11), Generative Adversarial Network (GAN) (0.16 and 0.12), and Gated Recurrent Unit (GRU) (0.16 and 0.125). The recall results are even more outstanding, with values of 0.25 and 0.35 at k = 5 and k = 10 for the proposed model, far surpassing other models (DQN: 0.11 and 0.19, MLP: 0.13 and 0.195, GAN: 0.14 and 0.2, GRU: 0.145 and 0.22). In terms of F1 metrics, the proposed model also performs excellently, reaching 0.18 at k = 5 and 0.2 at k = 10. In comparison, other models have significantly lower F1 values at k = 5 and k = 10. For example, DQN: 0.11 and 0.12; MLP: 0.13 and 0.133; GAN: 0.148 and 0.15, GRU: 0.152 and 0.16.

From the experimental results, the proposed personalized learning path decision-making method demonstrates superior performance through accurate prediction of knowledge point difficulty and dynamic adjustment of learners' knowledge point mastery. The data results show that the proposed model significantly outperforms other neural network models in precision, recall, and F1 metrics, particularly in recall, reaching a high value of 0.35 at k = 10. This indicates that the proposed model can not only recommend learning content more accurately but also cover the knowledge points those learners need more comprehensively, enhancing the overall effectiveness of the recommendation system.

In summary, the effectiveness of the research in this paper has been fully verified, showing that the method has strong practicality and advancement on intelligent education platforms, significantly improving the quality of personalized learning path decision-making and providing learners with a more precise and effective personalized learning experience.

5 CONCLUSION

This paper proposes a machine learning-based personalized learning path decision-making method on an intelligent education platform, aiming to enhance the effectiveness of personalized learning. The research content is divided into two main parts: first, accurately assessing the difficulty of each knowledge point through machine learning algorithms to provide a foundation for personalized learning; and second, dynamically adjusting the learning path based on learners' knowledge point mastery to achieve efficient decision-making for personalized learning paths. Experimental results show that the proposed model significantly outperforms other neural network models and collaborative filtering recommendation algorithms in precision, recall, and F1 metrics, especially in recall, significantly improving the coverage and accuracy of learning content recommendations.

The research in this paper has important value in the field of intelligent education. By introducing machine learning algorithms to predict the difficulty of knowledge points, the proposed model can more accurately identify learners' needs and provide personalized learning content. Additionally, by dynamically adjusting based on learners' knowledge point mastery, it ensures the optimization of the learning path and maximizes learning outcomes. This method not only enhances the accuracy and coverage of recommendations but also effectively improves learners' learning experience, with high practical application value.

Although the proposed model performed excellently in experiments, there are still some limitations. First, the model's performance depends on the quality and quantity of training data. If the data is not rich enough or contains noise, it may affect the prediction accuracy of the model. Second, the decision-making process of personalized learning paths is complex and requires substantial computational resources, which may face performance bottlenecks in large-scale applications. Furthermore, the model does not fully consider learners' emotional and motivational factors, which also play an important role in the actual learning process. Future research can be improved and expanded in the following directions: first, further optimize the model structure and algorithm to improve computational efficiency under large-scale data; second, introduce emotional computing and motivation theory to comprehensively consider learners' emotional states and motivational factors, enhancing the degree of personalization in recommendations; and third, strengthen data preprocessing and cleaning techniques to ensure the high quality and reliability of training data.

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7 AUTHOR

Yan Zhang is employed at the artificial intelligence division of HEBI POLYTECHNIC. His educational credentials include a Master's degree from Soochow University, specializing in signal and information processing (E-mail: zly570725@163.com; ORCID: https://orcid.org/0009-0001-2369-2797).