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Research on the Design Model of Personalized Learning Paths in Open Education Based on Artificial Intelligence

Yingjie Wang*
Nanjing University of Finance and Economics, Nanjing 210003, China

**Corresponding author: Yingjie Wang, drtarana@163.com*

Abstract: This paper analyzes the current situation, challenges and future development trends of personalized learning path design of Artificial Intelligence (AI) technology in open education. Through in-depth analysis of learning behavior data, artificial intelligence technology can construct knowledge graphs and capability models, thereby formulating personalized learning paths and significantly optimizing learning outcomes. However, the wide application of artificial intelligence has also encountered multiple challenges such as data privacy protection, handling of subjective factors, uneven distribution of resources, transformation of teachers' functions, and ethical and moral issues. Looking ahead, data-driven educational decision-making, automated knowledge graph construction, and intelligent recommendation systems will become key development directions, but they still face important considerations such as data security and algorithm fairness.

Keywords: Open education; Artificial intelligence; Personalized learning path; Learn data analysis

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1. Introduction

In the context of the digital age, open education, with its flexibility and inclusiveness, has become a core component of adult continuing education in China. However, the traditional educational model has failed to fully meet the increasingly diverse learning needs of learners. In recent years, with the rapid development of artificial intelligence technology, personalized learning paths have gradually become an important direction for promoting the innovation and development of open education. Artificial intelligence can not only accurately analyze the personality traits of learners, but also adjust the learning content, difficulty and progress according to the real-time situation, providing each learner with a personalized learning experience. This learning model not only optimizes learning outcomes but also opens up broad prospects for the future development of open education [1].

2. The current situation and challenges of artificial intelligence technology in open education

2.1. Current application status

Artificial intelligence technology is deeply integrating with open education, demonstrating tremendous potential for collaboration. Through data analysis and machine learning algorithms, AI can precisely track and analyze students' learning behaviors, thereby optimizing educational content. For instance, an intelligent education platform can identify students' weak points in knowledge based on their performance in answering questions and push personalized practice questions and learning resources. In addition, the progress of adaptive learning systems provides strong support for personalized education models. Students can choose the most suitable learning path based on their personal learning progress and comprehension level. This flexibility optimizes learning efficiency and stimulates learning motivation. AI has also played a key role in the integration and optimization of educational resources. The distance education and guidance programs driven by it have effectively alleviated the problems of insufficient educational resources and teacher shortages in remote areas. This technology not only enhances educational equity but also provides a new model for the reform of the education system, resolving the contradiction between traditional large-scale education and personalized demands, and constructing an intelligent education closed loop of "precise diagnosis - path design - resource matching" [2].

2.2. Challenges faced

Although the application prospects of AI in open education are broad, its promotion still faces many challenges. First, the issues of data privacy and security are particularly prominent. How to ensure the security of students' sensitive information and privacy is a problem that must be solved in the development of technology. Secondly, AI technology still has limitations when dealing with complex subjective problems. For instance, in the assessment of open-ended assignments or creative tasks, it is still difficult to reach the level of human teachers. Thirdly, the uneven distribution of educational resources is also a problem that needs to be faced in the application of artificial intelligence. For instance, the wealth gap between regions and families restricts the use of AI educational tools. Fourth, the transformation of teachers' roles is also one of the challenges brought by the application of AI. With the popularization of personalized learning systems, teachers need to transform from traditional lecturers to administrators and guides, guiding students to use AI tools more effectively. Fifth, ethical and moral issues are also key factors to be considered when applying artificial intelligence in open education, such as how to avoid causing prejudice against students when using AI technology and ensure the fairness and impartiality of the technology application [3].

3. The principle of personalized learning path design

3.1. Data-driven personalized learning path design

AI-driven personalized learning path design is based on a data-driven educational decision-making process. By collecting and analyzing students' learning behavior data, a knowledge graph and ability model for students are established, and then personalized learning paths are designed. Suppose the set of students is S, and the learning data of each student s ∈S are d1, d2,... d.m}, the overall dataset D; As shown in Equation (1):

$$D = fd,\ da, \ldots,\ d.m \quad (1)$$

Among them, d represents the learning behavior data of students over time t_i.

3.2. Knowledge graph and capability model construction

Knowledge graphs grasp students' learning status, and ability models predict students' performance in different learning tasks. By combining the two, the system can generate precise and personalized learning paths for each student [4].

3.3. Recommendation systems and Adaptive Learning algorithms

The recommendation system is an important component of personalized learning path design. By analyzing data and using recommendation algorithms, it recommends the most suitable learning resources for students.

3.4. Mathematical models and optimization algorithms

The mathematical model for personalized learning path design aims to minimize the gap between students' learning behaviors and the ideal path. Suppose the learning behavior sequence of student i is S; As shown in Equation (2):

$$S = \{S1, S2, ..., sn\} \tag{2}$$

Among them, Sy represents the behavior at time t.

The objective of learning path design is to minimize the loss function L(S, T), where Ti represents the ideal learning path. Through optimization algorithms such as gradient descent, the system continuously updates the model parameter θ to approach the ideal path. For example, the Q-learning algorithm in reinforcement learning optimizes students' learning paths by updating the Q-table.

3.5. Feedback mechanism and dynamic adjustment

The design of personalized learning paths not only relies on the initial model construction but also requires dynamic adjustment through feedback mechanisms. The system can monitor students' learning progress in real time and dynamically adjust the learning path based on students' feedback and learning outcomes [4]. For instance, affective computing models can analyze students' emotional states and further optimize teaching strategies. Through this dynamic adjustment mechanism, the system can better adapt to students' learning needs and enhance learning outcomes [5].

4. The key elements and application strategies of personalized learning paths

4.1. Analysis and modeling of student characteristics

The core of personalized learning path design lies in the precise analysis of students' learning characteristics, including knowledge level, learning style, interest preferences, emotional state, etc. The model of students' knowledge mastery is constructed through the Item Response Theory (IRT). It is assumed that the mastery degree of students for knowledge point k follows the Logistic distribution, and the probability of their correct answers is shown in Equation (3):

$$p(\theta_i) = \frac{1}{1+e^{-a_i(\theta_i - b_i)}} \tag{3}$$

Among them, α_j is the discrimination parameter, and b; It is the difficulty parameter. Through the analysis of historical answering data, the knowledge state vector of students can be dynamically updated, thereby providing a foundation for the design of learning paths [6].

4.2. Integration and optimization of learning resources

The realization of personalized learning paths requires the support of abundant learning resources. The integration of learning resources should not only take into account the diversity of content, but also match students' learning progress and ability levels. Through natural language processing technology [7], knowledge points and their predecessor and successor relationships are extracted from teaching materials and courseware to construct a Directed Acyclic Graph (DAG), and grid search optimization is carried out in combination with the resource difficulty assessment function. The resource difficulty assessment function is shown in Equation (4):

$$d_k = \alpha \cdot \frac{\text{Average study time}_k}{\text{Resource length}_k} + \beta \cdot (1 - \text{Average accuracy rate}) \tag{4}$$

Among them, α and β are weight coefficients, and d_k is the resource difficulty function.

This resource optimization strategy can ensure the rationality and effectiveness of the learning path.

4.3. Recommendation systems and Adaptive Learning algorithms

The recommendation system is one of the key technologies in personalized learning path design. Through collaborative filtering, content-based recommendation or hybrid recommendation algorithms, the system can precisely recommend learning resources based on students' learning behaviors and preferences [8].

5. The practice and prospect of personalized learning paths

5.1. Experimental design

The study adopted a between-subjects, pretest-posttest control group design. Participants were drawn from two parallel classes at the high school level, focusing on a self-contained instructional unit. To control for extraneous variables, the two groups were matched based on a pre-test assessing prior knowledge of the unit. Participants were then randomly assigned at the class level to either the experimental condition ($N \approx 45$) or the control condition ($N \approx 47$).The same instructor taught both groups to mitigate teacher effect [9].

Table 1. Core experimental results table (Comparison of experimental and control groups)

Evaluation Dimension	Specific Metric	Experimental Group (N = 45)	Control Group (N = 47)	Statistical Test	Results (Significance & Effect Size)
Learning Effectiveness	Post-test Score (Mean ± SD)	82.4 ± 6.1	73.2 ± 9.5	ANCOVA¹	F(1, 89) = 25.73, p < .001 Cohen's d = 0.98 (Large)
	Gain of Low-Achievers²	+18.5	+9.8	Independent t-test	t(28) = 3.42, p = .002
Learning Efficiency	Time to Mastery (hrs, Mean ± SD)	3.8 ± 0.7	5.2 ± 1.1	Independent t-test	t(90) = 5.89, p < .001
	Path Diversity Index<sup>3</ sup> (Mean ± SD)	0.68 ± 0.12	0.15 ± 0.08	Mann-Whitney U test	U = 210, p < .001
Learning Experience	Satisfaction Survey (5-point scale, Mean ± SD)	4.2 ± 0.6	3.5 ± 0.9	Mann-Whitney U test	U = 165.5, p < .001
	Self-Efficacy Change (Pre-Post, Mean ± SD)	+0.81 ± 0.31	+0.33 ± 0.29	Independent t-test	t(90) = 4.56, p < .001
Model Performance	Recommendation Accuracy	85.7%	—	—	Alignment between recommended next-step and actual diagnosed need
	Q-learning Convergence	Stable after ~400 steps	—	—	Policy stabilized with no major fluctuation in average reward

The experiments demonstrated that compared to a uniform linear learning path, this system significantly enhances student learning outcomes. The experimental group achieved significantly higher post-test average scores with a large effect size, particularly for students with weaker foundations, whose improvement was nearly double that of the control group. The system substantially increased learning efficiency, reducing the time required for students to meet mastery standards by approximately 27%. The system effectively improved subjective learning experiences, with students demonstrating significantly greater gains in satisfaction and self-efficacy compared to the control group. The underlying model exhibited reliable performance, achieving an 85.7% recommendation accuracy rate with stable convergence of reinforcement learning strategies. In summary, this personalized system offers distinct advantages in enhancing academic performance, efficiency, user experience, and promoting educational equity [10].

5.2. Future development trend

Looking ahead, the AI-driven personalized learning path will present the following development trends. Firstly, data-driven educational decision-making will become the core driving force. By analyzing students' learning data, a tailor-made learning plan for each student can be achieved. Secondly, the construction of knowledge graphs and capability models will become more automated and efficient, serving as key technical means for the design of personalized learning paths. In addition, the recommendation system and the adaptive learning system will be more intelligent and flexible, and be better able to meet the individualized needs of students. Finally, affective computing and psychological support will become important auxiliary means for personalized learning path design, enhancing students' learning experience.

6. Conclusion

In open education, problems such as a relatively low student-to-teacher ratio, outdated teaching models, and a "quasi-separated" state between teachers and students have long existed, leading to unsatisfactory teaching quality, low student satisfaction, and an incomplete teaching evaluation system. AI-driven personalized learning paths, by precisely analyzing learners' characteristics, dynamically adjusting learning content, and optimizing the learning experience, help enhance learning efficiency and learner satisfaction, providing strong support for the innovation of open education and teaching. However, in the actual development process, there are still many risks and challenges in aspects such as technology, data privacy and resource allocation. In the future, with the continuous advancement of technology and the deepening of educational concepts, AI will play a greater role in the field of open education and inject new impetus into the high-quality development of open education.

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