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Review of AI-Driven Algorithms for Identifying Students' Knowledge Strengths and Weaknesses and Personalized Learning

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Abstract. This paper reviews the research progress of AI-driven student knowledge strength and weakness identification and personalized learning algorithms. Firstly, it elaborates on the significant role of artificial intelligence technology in educational precision, pointing out the limitation of traditional educational models and the value of personalized learning systems in addressing these issues. By sorting out 24 related academic essays, it summarizes the core paths and corresponding algorithms for identifying students' strengths and weaknesses, and categorizes the implementation logic of personalized learning algorithms. In the experimental part, the performance of different algorithms is compared, including indicators such as accuracy, error rate, and stability. It is found that algorithms like gradient boosting machines and neural networks perform excellently in specific tasks. Finally, the paper analyzes the current limitations analyzes the current limitations in research, such as multimodal data fusion, intervention precision, ethical fairness, and cross-scenario adoptability. It also proposes future research directions that need to strengthen multimodal perception, ethical norms, cross-scenario integration, and dynamic intervention mechanisms, providing theoretical and methodological references for the digital transformation of education.

Keywords: AI-Driven Algorithm, Student Knowledge Weakness Identification, Personalized Learning, Adaptive Algorithm Optimization

1. Introduction

Currently, the development of artificial intelligence technology in the field of education has significantly promoted the process of educational precision and enhanced the possibility of realizing personalized learning in public education. The knowledge transmission mode of traditional educational models struggles to adapt to the degree of differences in students' individual cognition, leading to reduced learning efficiency and misallocation of educational resources. However, AI-driven personalized learning systems can conduct detailed analysis of students' learning data through algorithms, adjust teaching content and paths, and are expected to solve this dilemma.

Students' knowledge strengths and weakness are key factors and links in promoting personalized learning. Accurate identification of knowledge weak points can determine the effectiveness of

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learning assistance. By the detailed analysis of various reflective data on students' academic levels (such as homework, quiz, exams, etc.), their weak point in the acquisition of specific part of knowledge can be identified. As a result, by combing it with personalized learning algorithms, both educational resources and students' cognitive levels will be greatly improved.

Therefore, a systematic review of students' knowledge strengths or weaknesses and personalized learning algorithms can clearly indicate the current technological progress, and also provide theoretical and methodological references for precision practice in the digital transformation of education, which has important practical value.

According to existing research, knowledge strength and weakness identification faces some problems of difficult multimodal data fusion and low precision. It is proposed to use educational knowledge graphs as a tool to track the pre-requisite associated knowledge of weak points through high-order reasoning methods. A structure of combining "public learning network" and "personalized learning path" is constructed [1]. Currently, some technologies adopt knowledge tracing models to quantify knowledge mastery, combine computerized adaptive testing to accurately locate gaps, and allocate resources based on strengths and weaknesses [2]. In addition, the RADAR system integrates multi-dimensional data and identifies weak points through decision trees and CFS algorithms [3]. Through a path recommendation method combining the Fuzzy-CDP cognitive diagnosis model and Apriori algorithm, a closed loop of knowledge point remediation and resource matching is realized, improving mastery efficiency by approximately 20% [4]. At the meantime, AI-assisted learning analysis systems mark signals in real time, such as the MATHia system which locates specific knowledge gaps, and advocate balancing technical efficiency with teachers' experience [5].

The subsequent chapters of this paper mainly introduce related algorithm reviews, covering student knowledge strength and weakness identification and personalized learning algorithms, algorithm performance comparison, research limitations, and future research directions. Its goal is to present current technological progress of the studied algorithms and provide theoretical or methodological references for educational digital transformation, as well as guide future research for relevant researchers.

2. Review of related methods

2.1. Summary of algorithms for identifying students' knowledge strengths and weaknesses

In the algorithms for identifying students' knowledge strengths and weaknesses, homework-based identification and test-based identification are two core approaches.

2.1.1. Model for homework-based identification

The k-NN algorithm can analyze the types of errors in uploaded homework submission data, while the random forest algorithm can identify weak parts based on homework completion quality and frequency, following the logical chain of "collecting homework data→ extracting knowledge point features associated with homework → algorithm-based classification" [6] Furthermore, applying the random forest algorithm, which follows the process of "inputting homework accuracy rate and completion time→ mapping knowledge point labels → model training" to output the probability of students mastering specific knowledge points. Moreover, by the comparison of the RepTree, k-HH, and Naïve Bayes algorithms, and found that the RepTree algorithm achieved the highest accuracy

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(95.50%) in predicting students' academic performance, enabling effective identification of students at high risk of failing to master key knowledge points [7].

2.1.2. Model for test-based identification

By using a deep knowledge tracing model, which takes students' test answer sequences as input, models knowledge states through an LSTM network, and updates mastery probability in real time to identify unmastered knowledge points [8]. Also, the application of the Gradient Boosting Machine (GBM), which follows the process of "collecting test scores and knowledge points corresponding to wrong answers→ feature selection → model training" to output the ranking of knowledge strengths and weaknesses, achieving an accuracy of 98%. Moreover, by introducing a learning platform integrated with functions such as question-and-answer generation and weakness identification; this platform applies NLP and machine learning technologies to analyze students' test responses, thereby enhancing the accuracy of identifying weak knowledge points.

2.2. Summary of personalized learning algorithms

Personalized learning algorithms cover supervised learning, unsupervised learning, optimization algorithms, and deep learning, forming diverse implementation logics.

2.2.1. Supervised learning model

The Bayesian-optimized random forest (with an accuracy of 87%) and k-NN (with an accuracy of 73%) had better prediction effects; their algorithm process is "inputting features (academic scores, learning duration, etc.) → Bayesian optimization of hyperparameters → model training → outputting personalized performance prediction and knowledge point recommendations" [9]. The SVM and LR algorithms, which follow the process of "inputting training data (test scores and knowledge points labels) → kernel function mapping or logistic function transformation → classification model training → outputting knowledge point mastery levels" [10]. The application of random forest algorithm in personalized learning: in addition to identifying knowledge weaknesses, it can predict students' graduation and dropout status (with accuracy of 79.89%) and further recommend targeted learning strategies based on the predication results [11].

2.2.2. Unsupervised learning and clustering algorithms

Review of application of multiple algorithms in personalized learning, including the K-means and DBSCAN algorithms. These algorithms follow the process of "collecting students' learning behavior data → feature standardization → clustering → extracting group features → generating group-based personalized learning paths"; they also noted that reinforcement learning can be used to optimize learning paths, and emphasized that personalized learning plays a key role in improving students' learning engagement and academic performance [6]. Moreover, demonstration of a K-means application process: "inputting multi-dimensional data (age, academic score, etc.) → clustering → group feature analysis → recommending common learning strategies for the same group" [11].

2.2.3. Other relevant studies on personalized learning algorithms

Numerous studies have focused mainly on application and challenges of algorithms. For instance, Alqahtani et al. explored the application of NLP and large language models in personalized learning

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and automatic scoring, while mentioning the ethical challenges and bias risks that may arise during algorithm application [12]. Chopra & Arora focused on AI-enabled teacher support: they pointed out that adaptive systems and virtual assistants can optimize educational procedures, thereby helping teachers provide more targeted personalized guidance to students [5]. The analysis of the mechanisms of content recommendation and adaptive assessment in personalized learning, with practical cases from platforms such as Duolinggo and Coursera [2]. Gupta discussed the paths for AI to enhance interaction in engineering education, including the application of intelligent tutoring systems and predictive analysis in personalized learning design [13]. Khusnadin et al. warned of the risks of data privacy leakage and algorithm bias in personalized learning algorithms, and emphasized that educational counselors need to promote transparent algorithm application practices [14]. Abisoye constructed an analysis framework for STEM education-oriented personalized learning, which covers data processing, real-time assessment, and feedback loops to support the implementation of personalized learning [15]. Luo took ChatGPT as an entry point, discussed the impact of AI on traditional teaching methods, and proposed strategies to balance AI-driven personalized learning and traditional teaching [16]. Oyebola Olusola Ayeni et al. reviewed various technologies applied in personalized learning, with a special emphasis on the importance of ensuring ethics and fairness in algorithm design and application [17]. Ma et al. proposed a learning path recommendation model based on multi-algorithm collaboration, which combines association rules and swarm intelligence algorithms to optimize the matching between educational resources and students' learning needs [4]. Das et al. elaborated that AI-driven adaptive systems can realize personalized learning paths and real-time feedback through machine learning, NLP, and other technologies, while also mentioning the challenges of protecting data privacy and ensuring algorithm fairness [18]. Strielkowski et al. pointed out that AI adaptive learning (a core form of personalized learning) promotes the sustainable transformation of education, and the epidemic has accelerated its development; however, attention must be paid to ethical issues and privacy protection in the application of related algorithms, and these issues require continuous attention from researchers and educators [19].

3. Comparison of algorithms performance

Table 1 presents a comparative analysis of the performance of several highly accurate algorithms. GBM (Gradient Boosting Machine) stands out with an impressive 98% accuracy, accompanied by strong stability (AUC 0.97) and relatively low error rates (MAE 0.03, MSE 0.03, RMSE 0.1). RF (Random Forest), DT (Decision Tree), and MLP (Multilayer Perception) all achieve a 96% accuracy rate. RF and MLP show good stability with an AUC of 0.98, though their error metrics vary. DT has a slightly lower stability but comparable error rates to GBM in some aspects. GNB (Gaussian Naive Bayes) and LR (Logical Regression) have a 90% accuracy, with similar error rates but relatively lower stability as indicated by their AUC values. Overall, GBM demonstrates superior comprehensive performance, while the choice of algorithm should also consider specific application scenarios and stability requirements.

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Table 1. The comparison among the performance of highly accurate algorithms

Name of Algorithms	Accuracy	Stability	Error rate
GBM (Gradient Boosting Machine)	98%	AUC 0.97	MAE 0.03 MSE 0.03 RMSE 0.1
RF (Random Forest)	96%	AUC 0.98	MAE 0.09 MSE 0.04 RMSE 0.21
DT (Decision Tree)	96%	AUC 0.93	MAE 0.03 MSE 0.03 RMSE 0.1
MLP (Multilayer Perception)	96%	AUC 0.98	MAE 0.09 MSE 0.09 RMSE 0.3
GNB (Gaussian Naive Bayes)	90%	AUC 0.96	MAE 0.09 MSE 0.09 RMSE 0.3
LR (Logical Regression)	90%	AUC 0.95	MAE 0.09 MSE 0.09 RMSE 0.3

4. Discussion

4.1. Limitations of the current research

Current personalized learning driven by AI faces multiple critical limitations. In terms of multimodal fusion and precise evaluation of learning beavior data, existing learning assessment models predominantly reply on single-modality data (e.g., answer results), lacking comprehensive utilization of, ulti-dimensional data, which fails to accurately extract students' learning features and patterns [1]. Moreover, multimodal learning behavior data (such as audio - video, text, and interaction data) suffer from problems like insufficient labelling and low fusion consistency. General-pirpose processing methods struggle to adapt to dynamic and complex teaching scenarios, resulting in inadequate behavior perception accuracy [1].

Regarding the accuracy of learning problem tracing and intervention, most current intervention research focuses on the recommendation of weak knowledge points, lacking in=depth tracing of problems or their causes and customization of personalized solutions. The ineffective convergence of existing large-model data with learning data and behavior data leads to limited intervention precision [1].

Ethical ad fairness issues also pose significant challenge. AI–driven personalized learning encounters common ethical challenges such as data privacy and algorithmic bias. Students' data collection and analysis may trigger leakage risks [13]. Additionally. if algorithms are trained on biased data, they may exacerbate educational inequality, resulting in low recommendation accuracy for specific groups (e.g., rural areas) [14].

In term of technology integration and cross-scenario adaptability, although AI tools in engineering education can enhance certain interaction, they show weak adaptability in common scenarios like experimental operations and collaborative projects, failing to achieve seamless connection of multi-scenario data [13]. This indicates that most existing technology applications are confined to single scenarios, lacking dynamic adaptation across scenarios [13]. These limitations collectively impede the further advancement and widespread adoption of AI-enhanced personalized learning in education.

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4.2. Future research directions

To improve AI-driven personalized learning in education, several key directions merit exploration. For enhancing the perception and fusion precision of multimodal learning behaviors, there is a need to develop multimodal data processing technologies tailored to teaching scenarios. This can involve introducing teaching and learning behavior perception prompt engineering to fine-tune pre-trained models, addressing the issue of insufficient labeled data. Additionally, constructing a modality-decoupled contrastive network and spatiotemporal alignment pre-training tasks enables high-precision fusion of time-sensitive and non-sensitive data, improving behavior perception consistency in dynamic interaction scenarios [1].

In term of strengthening ethical norms and fairness protection, establishing an ethical framework for AI educational applications is essential. Measures include anonymizing data, controlling access permissions to safeguard privacy, and adopting fairness - aware algorithms to reduce bias. Collaboration should also be carried out to formulate standards for data use and algorithm auditing, ensuring that AI - driven personalized learning does not exacerbate educational inequalities [14].

To promote cross-scenario technology integration and subject adaptation, developing cross-scenario adaptive learning systems is advisable. This entails creating integrated virtual laboratories, collaborative tools, and other scenario-related data, as well as developing multimodal assessment models. Moreover, migrating existing learning optimization-related algorithms can enhance adaptability across different disciplines and learning stages, facilitating personalized support that transitions from knowledge imparting to ability cultivation.

Regarding constructing precise tracing and dynamic intervention mechanisms, a tracing model that integrates knowledge racing and anormal behavior analysis should be established. Based on educational knowledge graphs, a causal structure diagram for predicting source knowledge points can be built. By comparing individual and group behavior saliency maps, the causes of abnormal learning behaviors can be located. Reinforcement learning can then be applied to dynamically optimize intervention strategies, adjusting learning paths and resource recommendations in real-time according to students' cognitive states [1]. Collectively, these initiatives can help overcame the current limitations of AI-enabled personalized learning and drive its more effective implementation in educational contexts.

5. Conclusion

AI-driven algorithms for identifying students' knowledge strengths and weaknesses and personalized learning have achieved significant progress in the field of educational precision. By analyzing homework and test data and applying diverse algorithm models, dynamic assessment of students' knowledge status and overall recommendation of personalized learning paths have been realized. Form the perspective of performance in accuracy. Strategies such as Bayesian optimization can further improve model effects, providing powerful tools for educational practice.

However, current research still has limitations: insufficient fusion of multimodal learning behavior data leads to limited perception accuracy; intervention strategies lack in-depth tracing of the causes of problems; data privacy and algorithmic bias trigger ethical and fairness concerns; and it is difficult for technical applications to adapt to complex teaching needs across scenarios.

Future research can mainly focus on four major directions: first. develop multimodal data fusion technologies to improve the consistency of behavior perception in dynamic scenarios; second, establish ethical norms and fairness algorithms to protect data privacy and educational equality; third, promote cross-scenario technology integration to enhance adaptability across different disciplines and learning stages; fourth, construct a tracing model that combines knowledge tracing and abnormal analysis, and realize dynamic and precise intervention through reinforcement learning. These breakthroughs will promote the upgrade of AI educational applications from “knowledge identification” to “competence development”, providing solid theoretical and practical support for the digital transformation of education.

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