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Research on the Construction of a Precision Teaching Model Based on Big Data

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Abstract: With the explosive growth of educational big data, traditional experience-driven teaching models have gradually transitioned toward data-driven instruction. However, existing precision teaching research commonly faces bottlenecks such as limited data dimensions, inadequate algorithm adaptation to teaching scenarios, and static teaching strategies. In light of this, this study aims to construct a dynamic adaptive precision teaching model based on the integration of multimodal educational big data. It further designs a closed-loop operational mechanism comprising "multi-source data analysis – precision teaching implementation – data feedback iteration". First, learner data is integrated from multiple sources—including LMS systems, behavioral tracking technology, and sensor devices—to construct a comprehensive digital learner profile. Second, a precision teaching model is built using Graph Neural Networks (GNN), embedding educational psychology theories and subject-specific pedagogical principles into the algorithm's core architecture to achieve a layered adaptive algorithm design. Finally, we propose a dynamic adaptive model based on rule-based reasoning and reinforcement learning, which can optimize teaching strategies in real time according to the dynamic changes in learning behavior. Experimental results on our self-built dataset of authentic educational practice scenarios demonstrate that this model significantly enhances teaching precision and learner learning efficiency, fully validating its technical feasibility and application effectiveness.

Keywords: Big Data; Precision Teaching; Learner Profiling; Reinforcement learning; Knowledge Tracking

1. Introduction

The explosive growth of structured, semi-structured, and unstructured educational big data has transformed current teaching models from traditional theory-and-experience-based approaches to data-driven, scientifically precise methodologies, breaking away from conventional one-size-fits-all instruction [1]. However, existing precision teaching research still faces significant limitations, struggling to implement "teaching tailored to learning" plans that account for individual differences. Consequently, achieving precision teaching through big data has become a core imperative in the field of educational technology.

Scholars both domestically and internationally have conducted preliminary explorations in precision teaching. Regarding dynamic decision-making algorithms, Ye and Liu [2] proposed utilizing multimodal large models combined with rule-based reasoning and reinforcement learning to translate education-related theories into an "if-then" rule library that constrains reward functions. This approach relies on multimodal data to iteratively refine teaching strategies in real time. However, this solution fails to address the quality disparity between subjective textual data and objective sensor data during data fusion, potentially leading to imbalanced strategy weight allocation. Zhang and Mou [3] proposed an algorithm based on LSTM neural networks and temporal analysis to capture sequential data such as student video viewing trajectories and mouse click frequencies. This enables the identification of dynamic features like declining attention or knowledge gaps, triggering corresponding strategies. However, this model does not cover non-digital learning behavior data processing, and its strategy adjustment thresholds employ uniform standards, lacking personalized settings. In terms of model architecture design, Qu [4] established a three-tier framework -

"infrastructure layer, data resource layer, service application layer"-based on information ecosystem chain theory. This integrates four data categories: teaching, services, campus card systems, and user behavior. It employs fuzzy recommendation models to match learning needs. However, evaluation-related functions like online exams and course assignments account for less than 0.2% of the system, resulting in a broken "learning-assessment" loop. Zhang et al. [5] focused on blended learning scenarios, proposing an "SPOC + Flipped Classroom" model. This approach decomposed modular resources for university English instruction and incorporated a multi-dimensional evaluation system, achieving a satisfaction rating of 3.72/5. However, the model faced challenges with poor adaptability for computer-based summative assessments, resulting in low acceptance among some students. In terms of multimodal technology integration, Qushem et al. [6] combined tools such as AI and VR/AR to achieve cognitive-emotional collaborative diagnosis through multi-source data including text and physiological signals, covering scenarios from K-12 to higher education. However, the high R&D costs of immersive devices and difficulties in terminal adaptation for some rural schools remain challenges. Tan et al. [7] combined micro-videos with frequency construction to design a "short video input - timed sprint - error correction" process, enhancing statistical skill proficiency. However, the intervention's effectiveness was limited to immediate assessment, with no significant improvement in skill transferability. Feng and Lv [8] developed education-friendly algorithms and integrated subject-specific cognitive logic into general algorithms via federated learning. This enabled distributed training across multiple classes, reducing strategy adaptation differences between urban and rural school settings by 35%. However, this approach requires separate algorithm development for each subject, resulting in high R&D costs. In cognitive diagnosis and predictive early warning, Wei et al. [9] constructed the PI-MCDM model, integrating BP neural networks to eliminate response interference and achieving a three-tiered diagnosis ("shallow-mid-deep"). This approach demonstrated higher diagnostic accuracy and satisfaction than traditional models, though it exhibited limited capability in processing subjective question data. Tsai et al. [10] employed statistical learning (logistic regression) and deep learning (multi-layer perceptron) to construct a dropout prediction model using variables such as academic dynamics and absence frequency. While achieving 77% accuracy with deep learning, the model excluded latent variables like family background and learning motivation, resulting in limited predictive dimensions. Wang [11] developed an Adaptive Learning System (ALS) integrating the DINA cognitive diagnosis model with a CNN-LSTM affect recognition algorithm. This system enables knowledge gap identification, dynamic strategy adjustment, and affective state recognition. However, its operational action recognition accuracy in complex practical training scenarios was only 73%, and affect recognition proved susceptible to environmental lighting and occlusion, indicating insufficient robustness.

Current research exhibits three primary shortcomings: (1) Limited data dimensions: Constraints from single data sources hinder the creation of comprehensive, end-to-end learner digital profiles. (2) Inadequate alignment between algorithms and instructional contexts: Precision teaching algorithm models lack sufficient integration of pedagogical theories, limiting the effective generation of targeted teaching strategies. (3) Static teaching strategies: Most studies focus solely on strategy generation, neglecting the dynamic evolution of teaching approaches and failing to establish complete closed-loop mechanisms.

In summary, this paper proposes the construction of a dynamic adaptive precision teaching model based on multimodal educational big data integration. This model achieves learner digital profiling throughout the entire learning journey by fusing multimodal and cross-scenario data. It embeds pedagogical principles into customized algorithmic models, establishing a hierarchical adaptation algorithm to match precision teaching modes and avoid the homogenization issues inherent in large-classroom teaching. Finally, it establishes an optimized teaching strategy model featuring "real-time feedback - dynamic adjustment". Teaching outcomes are iteratively fed back to the data center, continuously refining algorithm parameters and model decision logic. This forms a complete closed-loop system: "multi-source data analysis - precision teaching implementation - data feedback iteration".

2. Introduction to Related Work and Technology

2.1 Related work

2.1.1 Full-path learner profiling research for multimodal data fusion

A crucial research direction in the field of educational technology is the development of learner digital profiling techniques. Existing methods include physiological signal analysis, behavioral analysis, and multimodal data fusion analysis. Physiological signal analysis primarily uses electroencephalogram (EEG) and heart rate variability (HRV) to objectively reflect cognitive load, but it requires specialized equipment and is highly invasive. Behavioral analysis infers learning styles by examining learning behaviors, yet it is susceptible to individual differences. Multimodal data fusion analysis combines multiple data sources to provide more comprehensive state assessments, though current approaches still face limitations in modal fusion strategies.

2.1.2 Customized algorithmic models incorporating pedagogical principles

Currently, sequence recommendation algorithms can embed the "step-by-step progression" principle of teaching into algorithmic models, enabling predictions of next-step learning needs based on students' learning sequences. However, these algorithms overly rely on historical data and tend to overlook sudden shifts in student interest. On the other hand, attention mechanisms can incorporate the "priority emphasis" principle into algorithmic models, allowing for the reinforcement of core knowledge point weights within the model. Yet this approach may lead to excessive focus on high-frequency content, resulting in a narrow learning coverage.

2.1.3 Dynamic adaptive and closed-loop iterative mechanism optimization strategy

Currently, existing dynamic adaptive teaching primarily relies on ensemble learning and reinforcement learning. Ensemble learning algorithms can generate personalized teaching strategies but require extensive data annotation. Reinforcement learning algorithms can continuously optimize teaching strategies through interaction with the environment, yet their training process is highly complex and prone to convergence difficulties. How to combine the strengths of different methods to achieve a balance for long-term optimization is a key focus of current research.

2.2 Related Technologies

2.2.1 Clustering analysis algorithm

Clustering analysis algorithms represent a crucial analytical method within unsupervised learning, enabling the automatic grouping of samples based on data similarity. This model employs the K-Means clustering algorithm to conduct a comprehensive analysis of learners' behavioral characteristics, identifying groups of learners with similar traits: foundational learners, capability-enhancement learners, and top-tier innovative learners. This provides a scientific basis for teachers to implement personalized instruction.

2.2.2 Classification algorithms

Classification algorithms represent a core technology in supervised learning, constructing mapping models from behavioral features to learning categories using labeled learning behavior data. Primarily employing algorithms such as logistic regression, SVM, and random forests, they accurately discern students' learning styles and academic risk levels. Logistic regression utilizes the sigmoid function to output class probabilities, SVM identifies the optimal classification hyperplane, while random forests enhance model robustness by integrating multiple decision trees.

2.2.3 Recommendation algorithms

Recommendation algorithm technologies encompass collaborative filtering and temporal recommendation techniques. Collaborative filtering technology extracts behavioral correlations within learner communities to provide individual learning potential data for precision teaching models. The temporal recommendation algorithm LSTM analyzes students' sequential learning behavior patterns to uncover underlying temporal patterns and cognitive development trajectories. It dynamically tracks the evolution of learning paths, establishes continuous trajectory models of students' cognitive states, and uncovers their latent learning needs.

2.2.4 Knowledge tracking algorithms

This model employs Bayesian Knowledge Tracking (BKT) and Deep Knowledge Tracking (DKT) based on Hidden Markov Models. Its core principle involves utilizing LSTM neural networks to automatically extract dependencies between knowledge points, while incorporating the self-attention mechanism from reinforcement learning models to achieve dynamic weight allocation. Furthermore, the Viterbi algorithm can be employed to generate the optimal sequence of a student's knowledge states. Model rules are then optimized using gradient descent or expectation maximization, enabling the inference of authentic changes in a student's knowledge mastery.

3. Framework Introduction

The model comprises three core modules, with low-latency, high-reliability information exchange between modules facilitated through standardized data protocols and encrypted interfaces.

3.1 Full-Path Learner Profiling Module

The specific architecture diagram of this module is shown in Figure 1:

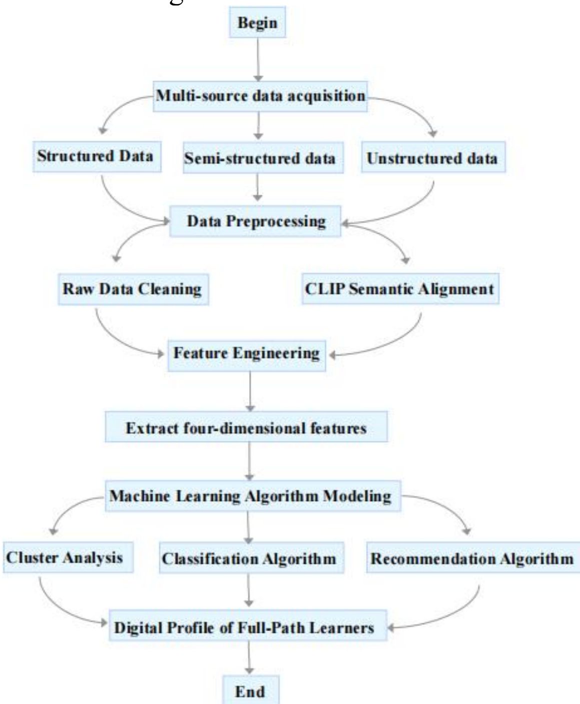

Figure 1. Full-Path Learner Profile Construction Architecture Diagram

3.1.1 Multimodal data acquisition and preprocessing

This model employs multiple technological approaches-including LMS, behavioral tracking, sensing devices, and image recognition-to comprehensively collect student data. Specifically: - LMS captures foundational student data, operation logs, and other unstructured content; - Behavioral tracking technology captures learning event types, timestamps, and students' micro-behavioral characteristics; sensor devices collect time-series physiological metrics like heart rate; and CNN-based image recognition quantifies behavioral indicators such as classroom attentiveness [12]. Finally, the model incorporates CLIP multimodal data fusion to standardize and align data, enabling deep cross-modal semantic associations that lay a robust foundation for subsequent modeling and analysis.

3.1.2 Feature engineering

Refine raw data into four-dimensional features suitable for modeling: knowledge mastery level, competency level, emotional state, and learning style.

Knowledge Mastery Level: Achieved through quantitative feature extraction and error pattern clustering. Its core lies in calculating the “Knowledge Point Mastery Level = Number of Correct Answers × Question Difficulty Coefficient / Total Number of Questions” using a custom formula. This method precisely reflects the true mastery level of knowledge points across varying difficulty levels by weighting harder questions.

Ability Level: Achieved through text feature processing and interactive feature construction, its core lies in utilizing NLP technology to analyze textual logical coherence, thereby extracting an “expressive ability” metric to quantify collaborative and learning capabilities.

Emotional State: Achieved through sentiment analysis to examine textual characteristics, its core lies in employing NLP sentiment analysis technology to parse textual data and extract semantic tendencies [13]. This enables the dynamic presentation of emotional fluctuations and attitudinal inclinations throughout the learning process.

Learning Style: Characterized through quantitative and interactive features, its core lies in analyzing learning focus habits using the formula “Focus Level = Effective Viewing Time / Total Playback Time”. This determines whether a learner is a deep immersion type or a fragmented learning type.

3.1.3 Machine learning algorithm modeling

① Clustering Analysis Algorithm:

This model analyzes student learning characteristics using the K-Means algorithm within clustering techniques, as follows: First, key quantifiable features such as knowledge point mastery, ability level, emotional state, and learning style are selected as the basis for group segmentation. Next, a K value is preset for K-Means, and cluster centers for “Foundation-Building Type”, “Progress-Driven Type”, and “Elite Breakthrough Type” are initialized. Finally, the Euclidean distance between each student's feature vector and the cluster centers is calculated. Students are assigned to the nearest cluster, and the centers are iteratively updated until convergence is achieved.

② Classification Algorithm:

This model classifies learning styles and academic risk levels using classification algorithms including logistic regression, SVM, and random forests, as detailed below: The logistic regression algorithm fits a linear relationship between features and category probabilities, using the sigmoid function to output probabilities of belonging to visual or auditory learning styles, or low, medium, or high risk. Random Forest integrates multiple decision trees, employing a majority voting mechanism to determine class assignments. This approach effectively mitigates the bias inherent in individual trees, enabling more robust identification of complex patterns such as “high risk”.

③ Recommendation Algorithm:

This model leverages collaborative filtering and temporal recommendation algorithms to uncover latent learning needs among students, laying the groundwork for precision teaching models. Specifically: Sequential recommendation focuses on the dynamic sequence of student learning behaviors. By capturing long-term and short-term dependencies in resource access order or learning trajectories, it models the continuous trajectory of cognitive development. Ultimately, it predicts students' potential learning needs in the next phase to provide a tailored precision teaching model.

④ Deep learning algorithms:

This model requires deep learning algorithms to further refine learner profiles. Specifically: On one hand, the model must enable the input layer to receive the aforementioned data. It utilizes a recurrent neural network (RNN) to analyze the temporal dependencies of learning behaviors and employs attention mechanisms to focus on key learning actions. On the other hand, the model employs backpropagation algorithms to optimize its parameters. This enables it to identify complex learning patterns and generate multidimensional profiles reflecting personalized learning strategy preferences.

3.2 Customized Algorithm Model Technology Incorporating Teaching Principles

The specific architecture diagram of this module is shown in Figure 2:

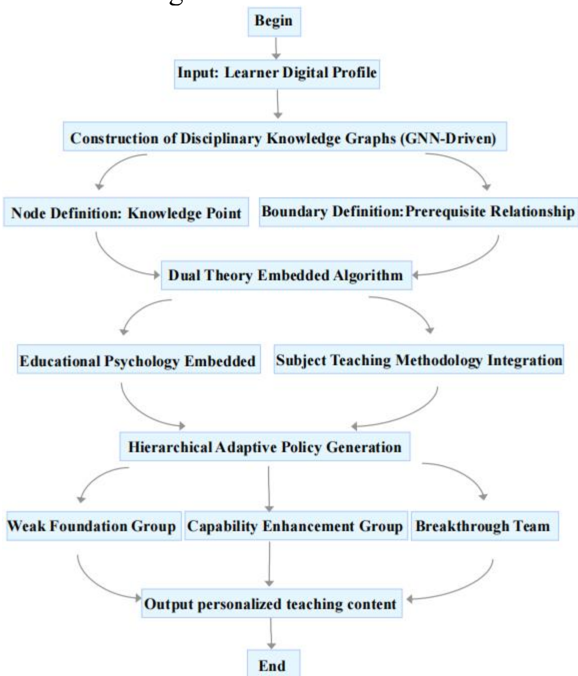

Figure 2. Customized Algorithm Model Architecture Incorporating Teaching Principles

3.2.1 Dual theory embedded algorithm core

Knowledge Tracking Algorithm: Utilizing Bayesian Knowledge Tracking (BKT) embedded within the “stimulus-response-reinforcement” mechanism of behaviorist teaching theory, this algorithm assesses students' comprehension levels of knowledge points based on their initial self-portraits. For instance, when the model calculates a student's mastery probability for a specific knowledge point falls below the threshold, it automatically triggers the supplementary practice module within the teaching model, forming a closed-loop control system of “practice-feedback-mastery”.

Reinforcement Learning Algorithm: This algorithm incorporates principles from constructivist pedagogy, such as “heuristic instruction” and “iterative optimization of teaching strategies”. It frames the teaching process as a dynamic decision-making sequence, using student learning outcomes as feedback rewards. For instance, the model adjusts question difficulty through reinforcement learning-escalating complexity when students answer correctly consecutively-mirroring the gradual guidance of Socratic dialogue in fostering critical thinking.

Integrated Learning Algorithm: This algorithm incorporates the “tiered instruction” concept from constructivist teaching theory. It primarily leverages XGBoost's feature processing and pattern recognition capabilities to categorize students into distinct instructional tiers, thereby constructing a precise tiered assessment model that enables personalized instruction.

Graph Neural Network Algorithm: This algorithm incorporates the “framework teaching method” concept from constructivist pedagogy. Graph Neural Networks (GNNs) can construct subject knowledge graphs and embed “knowledge progression” patterns-such as mapping prerequisite relationships between knowledge points-to plan rational learning paths for students from foundational to advanced levels. This effectively promotes each student's sustained development within the constructivist learning framework.

3.2.2 Output precise teaching models

①Students with Weak Foundations: For students with weak foundations, this model primarily employs a precision teaching model based on a three-step strategy: “Diagnosis - Gap Filling – Reinforcement”. The system employs the BKT algorithm to diagnose and identify knowledge gaps, leveraging subject knowledge graphs to pinpoint students' prerequisite concepts. This enables the targeted generation of subsequent instructional content. Simultaneously, it utilizes the behaviorist “stimulus-response” mechanism to progressively enhance knowledge mastery and reinforce learning outcomes.

②Capability Enhancement Students: For capability enhancement students, this model primarily implements a precision teaching model based on the progressive strategy of “Expansion-Deepening-Transfer”. Leveraging association rules from knowledge graphs, it recommends cross-chapter comprehensive application problems. Through reinforcement learning algorithms, it dynamically adjusts problem difficulty to guide students toward heuristic thinking.

③Top-tier Innovative Students: For top-tier innovative students, this model primarily provides a precision teaching framework centered on the advanced “inquiry-innovation-challenge” strategy. By analyzing learner profiles, the model matches students with open-ended problems and research-based learning tasks. Additionally, it leverages graph neural network algorithms to generate cutting-edge supplementary resources. Integrating these components into the precision teaching model stimulates students' critical thinking and innovative capabilities.

3.3 Dynamic Adaptive and Closed-Loop Iterative Mechanism Optimization Technology

The specific architecture diagram of this module is shown in Figure 3:

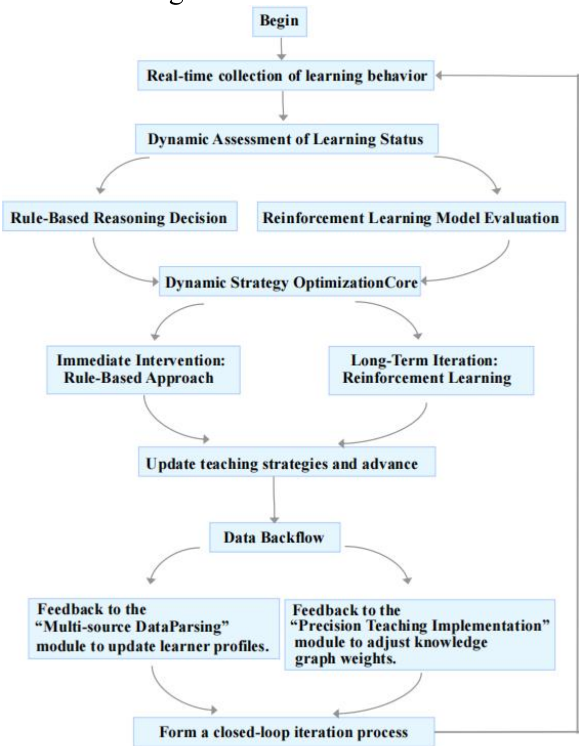

Figure 3. Architecture Diagram of Dynamic Adaptive and Closed-Loop Iterative Mechanism

3.3.1 Dynamic assessment of learner status

Achieving dynamic assessment of learner status can leverage the BKT model's parameter adjustment rules for reasoning judgment, combined with DKT deep knowledge tracking and GCN-driven knowledge graph dynamic modeling evaluation.

The BKT model's parameter adjustment can adapt its specific parameters to different scenarios. It can modify its internal parameters based on students' real-time response behavior.

In such cases, the system initiates a “confidence decay” logic decision. When abnormal response indicators are detected, it automatically increases the weight of the “guessing parameter” while correspondingly decreasing the weight of the “learning parameter”. This parameter adjustment within the BKT model fundamentally reduces the probability of attributing a single correct response to “true mastery”, thereby preventing misjudgments by the model.
DKT (Deep Knowledge Tracking) technology employs Long Short-Term Memory (LSTM) networks to process students' recent learning behaviors, enabling dynamic modeling of knowledge state evolution. For example, the DKT model can treat continuous learning interaction data as time-series inputs while capturing and retaining the underlying, time-varying cognitive states through the LSTM's internal state.
The implementation of GCN-driven knowledge graph dynamism manifests in two dimensions: First, both node and edge weights within the graph are designed as parameters dynamically updated based on student learning progress. Second, the system refreshes mastery weights for knowledge nodes at extremely short intervals using recent student learning interaction data, simultaneously calculating and adjusting the “dependency strength” of connecting edges between nodes.
3.3.2 Dynamic generation of teaching strategies
In terms of rule triggering, this model is designed to continuously and dynamically collect learners' digital profiles. The data is then fed back into a random forest ensemble algorithm, which undergoes parallel training to generate numerous decision trees. These trees produce predictive results that undergo voting or weighted averaging, thereby updating more robust and precise student status assessments (such as ability stratification and academic risk alerts). Based on this ensemble outcome, the system can dynamically trigger appropriate teaching strategies according to predefined rules.
In terms of long-term iteration, this model is designed to utilize reinforcement learning algorithms to select appropriate actions (such as adjusting teaching pace during instructional model construction) based on varying environmental states (students' mastery of knowledge points, ability levels, emotional states, learning styles). Simultaneously, it receives reward signals upon student learning completion, enabling the model to progressively learn an optimal strategy function through repeated experimentation with teaching approaches and observation of their learning outcomes (rewards). This strategy function guides the system to implement tailored instructional interventions across student states, thereby maximizing long-term learning gains.

4. Experiments and Analysis

4.1 Experimental Environment and Dataset

Experimental Environment: This experiment is deployed on a Kubernetes-based microservices architecture, utilizing Python 3.8 as the primary development language. The core algorithms rely on PyTorch, Scikit-learn, and XGBoost libraries. To simulate real teaching scenarios while ensuring data privacy, we employ a federated learning framework for distributed model training and inference across edge servers at five partner schools.
Dataset: This study is based on a self-built authentic educational practice dataset covering mathematics subjects in junior and senior high schools. Data sources include the Learning Management System (LMS), behavioral tracking system, and classroom sensors. Anonymized data from 12,500 students was collected over one semester. The dataset includes:
(1) Learning behavior data: Over 4.5 million answer records and video viewing logs.
(2) Multimodal data: Processed classroom attention indices (based on CNN image recognition), heart rate variability (HRV) data from selected volunteer students.
(3) Knowledge Graph: A mathematics knowledge graph has been constructed, comprising 285 knowledge node points and 712 relationship edges.

4.2 Experimental Design and Evaluation Metrics

4.2.1 Experimental design:
To validate the effectiveness of the proposed ensemble model, we designed the following comparative experiments:
① Experimental Group: Utilizes the dynamic adaptive model proposed herein. The system plans learning paths via GNN based on real-time learner profiles and dynamically generates

teaching strategies through reinforcement learning.

② Control Group 1: Employed a static recommendation model that performs one-time stratification and resource recommendations based on students' historical overall performance, lacking dynamic adjustment capabilities.

③ Control Group 2: Adopted a uniform teaching strategy where all students received identical instructional content and pacing.

The experiment spanned 8 weeks, focusing on two core units: "Quadratic Equations" and "Introduction to Functions".

4.2.2 Evaluation metrics:

Learning Effectiveness Metrics:

① Unit Test Pass Rate: The percentage of students who pass the standardized test at the end of each unit.

② Knowledge Mastery Improvement Value: The change in students' average mastery probability before and after experiments, calculated using the BKT model.

③ Learning Efficiency: Average learning duration required to achieve the same level of mastery.

Model Performance Metrics:

① Strategy Recommendation Accuracy: Proportion of expert teachers who blindly evaluate and endorse the effectiveness of strategies pushed by the system.

② System Response Latency: Average end-to-end delay from data collection to strategy delivery.

4.3 Experimental Results and Analysis

4.3.1 Comparative analysis of learning efficacy

As shown in the Table 1, the experimental group significantly outperformed both control groups across all learning efficacy indicators.

Table 1. Comparative Analysis of Learning Efficacy Evaluation Indicators

Evaluation Indicators	Experimental Group (Dynamic Adaptive)	Control Group 1(Static Model)	Control Group 2 (Standardized Instruction)
Unit Test Pass Rate	92.5%	80.1%	75.3%
Knowledge Mastery Improvement Value	+0.41	+0.28	+0.19
Average study duration (minutes)	105	132	150

①Effectiveness Analysis: The experimental group achieved a pass rate of 92.5%, significantly higher than the 80.1% of Control Group 1 and the 75.3% of Control Group 2. This demonstrates that the dynamic adaptive model can more precisely meet student needs, avoiding the resource mismatch issues caused by one-size-fits-all teaching approaches.

②Efficiency Analysis: Students in the experimental group achieved the predetermined mastery goals in the shortest average time (105 minutes), saving 30% of the time compared to the uniform instruction group. This indicates that personalized path planning and dynamic strategies effectively reduced students' ineffective learning time and alleviated cognitive load.

4.3.2 Effect analysis of layered adaptation strategy

We conducted a detailed analysis of the improvement levels among students within different groups:

Foundation Group: Demonstrated the most significant increase in knowledge mastery (+0.52). The model successfully traced back to foundational knowledge via the knowledge graph and pushed prerequisite concepts, effectively filling knowledge gaps.

Skill Enhancement Group: Achieved a 35% increase in accuracy on application-based questions with support from the model's "method summaries" and "key practice exercises".

Top-tier Breakthrough Group: 85% of students completed advanced challenge questions and demonstrated heightened learning engagement. GNN-driven cross-concept reasoning successfully delivered appropriate extension materials.

4.3.3 System performance analysis

Strategy Recommendation Accuracy: Expert evaluations confirm the system's overall strategy accuracy reaches 88.7%, demonstrating exceptional performance in identifying the "zone of proximal development" and providing "scaffolding".

System Response Latency: Supported by edge computing nodes, end-to-end average latency remains stable at 280 milliseconds, enabling near-real-time feedback for instructional interventions and meeting classroom continuity requirements.

4.4 Discussion of Results

The results of this experiment demonstrate that the dynamic adaptive precision teaching model proposed in this study exhibits significant advantages in enhancing learning effectiveness and efficiency. Its success is primarily attributed to the following three factors:

(1) Effectiveness of multimodal data fusion and dynamic profiling: Through cross-modal alignment using technologies like CLIP, the system achieves comprehensive, in-depth perception of learner states, providing a reliable data foundation for precise decision-making.

(2) Superiority of the Teaching Principle-Embedded Algorithm: By embedding behaviorist reinforcement mechanisms, cognitivist structured pathways, and constructivist scaffolding into the algorithm's core, the model transcends being a mere prediction tool to become an “intelligent tutor” that adheres to educational principles.

(3) The necessity of a closed-loop dynamic iteration mechanism: Compared to static models, this model can dynamically adjust strategies in real time based on students' evolving learning patterns. This creates a virtuous cycle of “multi-source data analysis → precision teaching implementation → data feedback iteration,” which is key to its significantly enhanced effectiveness.

5. Conclusion

The results of this experiment demonstrate that the model can significantly enhance teaching precision and learner effectiveness in real educational settings, while also validating its technical feasibility and application efficacy. However, this research still holds room for improvement in deep understanding of unstructured interactive data and cross-disciplinary universality. Future work will focus on integrating cutting-edge technologies such as large language models to enhance semantic comprehension of complex learning contexts and generative teaching capabilities. This will further explore the model's applicability across broader disciplines and educational scenarios, advancing precision teaching toward deeper levels of “human-machine collaborative integration”.

Acknowledgments

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