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Research on Large Model-Driven Precision Learning Intervention Models for College Students

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Abstract: The current large-scale teaching model in Chinese universities struggles to accommodate individual student differences, resulting in delayed and imprecise traditional learning interventions that fail to meet the urgent demand for personalized talent development in the era of intelligent education. This study proposes a large model-driven precision learning intervention framework. By integrating multimodal data, student profiling tags, and course knowledge graphs, the model enables granular cognitive diagnostics of students' knowledge gaps. Leveraging large models for natural language generation, it generates personalized intervention strategies, effectively transforming teaching paradigms from "mass-scale" to "personalized." This approach provides crucial theoretical guidance for universities to establish precision teaching intervention systems and enhance talent cultivation quality.

Keywords: Study interventions; Refinement; Large language models; Knowledge graphs; Student profile tags

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1. Introduction

With the advancement of educational informatization, students' personalized needs have become increasingly prominent. Future talent cultivation will shift from large-scale standardized training to personalized, customized development [1]. China's Education Modernization 2035 explicitly proposes leveraging modern technology to reform talent cultivation models, effectively integrating mass education with personalized development [2].

Currently, China's higher education institutions predominantly employ scaled teaching models. This uniform instructional path and pace fail to account for differences in students' knowledge foundations, learning abilities, and interests/motivation. It also lacks effective, continuous monitoring of non-cognitive factors such as students' emotional states (e.g., anxiety, frustration), resulting in subsequent traditional learning interventions being delayed and imprecise. Higher education institutions urgently require a precision learning intervention model capable of real-time perception of student learning states, accurate diagnosis of cognitive root causes, and dynamic generation of personalized support plans.

Breakthroughs in generative AI—such as the contextual understanding and knowledge emergence capabilities demonstrated by large language models like DeepSeek—provide a multidimensional intelligent framework for this educational transformation. Grounded in the higher education teaching context, this research employs multimodal data fusion technology, student profile tags, and course knowledge graphs to achieve a precise diagnosis of student cognitive states. It leverages the natural language interfaces of large models to enable natural interaction with students and content generation. Together, these form the intelligent core of precision intervention, enabling continuous optimization of learning support. This model facilitates the transition from "mass-scale" teaching to "personalized" precision learning interventions, effectively enhancing teaching quality and student learning outcomes.

2. Research status

2.1. Multimodal data fusion

Traditional learning interventions rely solely on subjective teacher experience, exam scores, and homework accuracy rates—single quantitative metrics that struggle to capture the complexity of the learning process. Multimodal data fusion technology extends beyond daily student performance by integrating diverse modalities—including gesture posture, writing trajectories, log data (e.g., click traffic, page dwell time), physiological signals (eye tracking, EEG), and emotional states (facial expression recognition, speech sentiment analysis)—to construct multidimensional perception models of learning states. This cognitive upgrade enables the system to interpret students' emotional engagement, cognitive load, and thought trajectories, achieving a leap from "unidimensional assessment to multidimensional perception" [3].

2.2. Domain knowledge graph technology

A knowledge graph is a technology that models and stores knowledge using a graph structure, aiming to describe real-world entities (things, concepts) and their relationships. As a powerful knowledge representation tool, it demonstrates significant application potential across multiple fields such as education, medicine, and agriculture.

A knowledge graph primarily consists of three components: nodes, edges, and properties. Nodes represent entities or concepts, edges represent relationships between nodes, and properties describe the characteristics or attributes of nodes or edges. Knowledge graphs have revolutionized the education sector by enabling the transition from "standardized" to "personalized" education [4–6]. This includes:

(1) Traditional course knowledge is typically presented in chapter-based formats, obscuring intrinsic connections between knowledge points. Knowledge graphs can construct a comprehensive knowledge map encompassing all knowledge points within a course or even an entire major. This clearly illustrates dependency relationships between knowledge points, horizontal connections between courses and majors, and hierarchical relationships among knowledge points, courses, and majors. It provides students with a holistic, interconnected knowledge landscape, helping them build systematic cognitive frameworks.

(2) Traditional standardized teaching models force all students to follow identical learning paths, hindering personalized instruction. Knowledge graphs enable automated dynamic learning path planning. For instance, when a student struggles with "Knowledge Point B," the system traces the root cause to insufficient mastery of "Prerequisite Knowledge Point A." The system dynamically generates a new

learning path: master A first, then tackle B. Based on the student's current learning stage, the graph precisely recommends relevant learning resources—such as instructional videos, targeted exercises, and supplementary reading materials.

2.3. Large language models and their educational adaptation technologies

Large language models (LLMs) refer to deep learning models trained on massive datasets, featuring enormous parameter counts (typically billions or even trillions). These parameters enable the models to understand, generate, and process natural language. Their core technologies include: natural language understanding and generation, context learning, and knowledge reasoning. However, general-purpose large models often suffer from issues like "hallucinations" and insufficient domain expertise. Techniques such as prompt engineering, retrieval-enhanced generation, and fine-tuning are required to optimize them into qualified "intelligent learning companions."

In recent years, the application of large models in education has experienced explosive growth, extending from higher education to primary and secondary levels, becoming a core driver of digital transformation in education. Multimodal large models analyze students' learning behaviors and cognitive characteristics, combining dynamic reasoning from domain knowledge graphs to generate personalized learning paths for each student. This path reconstruction breaks the standardized supply model of traditional education, enabling "one-to-one" teaching organization [7–12]. For instance, AI analyzes students' cognitive patterns and ability structures to derive over a hundred personalized learning plans, truly realizing the vision of individualized cultivation.

See **Table 1** for the comparison of traditional teaching models and large model-driven precision teaching models.

Table 1. Comparison of traditional teaching models and large model-driven precision teaching models

Comparison	Traditional teaching model	Large model-driven precision teaching model
Data foundation	Single-source data (exam scores, assignment completion)	Multimodal, end-to-end, multidimensional data
Decision mechanism	Teacher experience-dependent	Data-driven, human-machine collaborative decision-making
Teaching organization	Uniform content, uniform pace	Personalized content, adaptive pacing
Assessment approach	Primarily summative evaluation	Formative, value-added, and holistic assessment
Teacher role	Knowledge transmitter, classroom controller	Learning facilitator, emotional supporter, instructional designer

3. Building a precision learning intervention model driven by large language models

3.1. Overall approach to model construction

The core concept of this model is to utilize large language models as the system's "intelligent brain." By leveraging its powerful semantic understanding, reasoning, and generation capabilities, it performs deep analysis on multidimensional data, integrating knowledge graphs and student profile tags. This enables a precise, automated closed-loop process from "perception" to "decision-making" and ultimately to "intervention."

The interactions among the system's components are illustrated in **Figure 1** below:

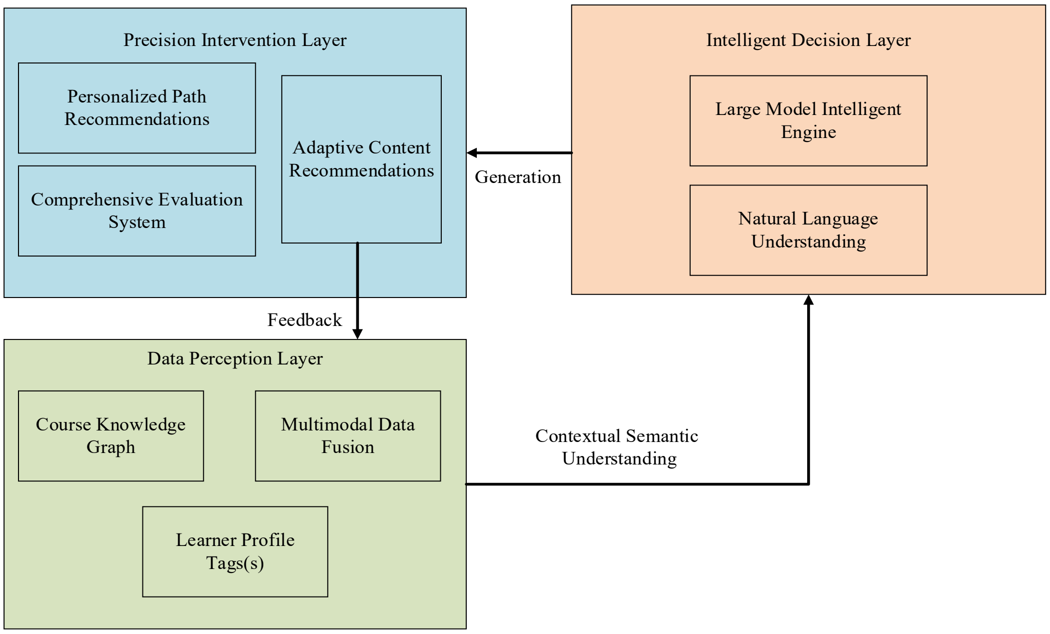

Figure 1. Large model-driven precision learning intervention framework

3.2. Model system framework

3.2.1. Student profile tagging based on multimodal data

By constructing a multidimensional data collection model (historical data, streaming data; see **Table 2**), we achieve comprehensive coverage of the following four data categories:

(1) Basic attribute modes: Including initial states such as grade level, major, and admission scores;

(2) Academic performance data: Knowledge mastery states such as course grades, assignment scores, and classroom participation;

(3) Learning behavior data: Offline behaviors include classroom attendance rates, library borrowing records, seating preferences, etc.; online behaviors include login frequency, video viewing duration, assignment submission timestamps, etc.

(4) Psychological and emotional modality: Includes non-verbal data such as head expressions and postures during class, hand gestures, eye-tracking patterns, and attention shifts.

Table 2. Classification and acquisition methods for multimodal teaching data

Data type	Specific content	Collection method	Educational value
Text data	Assignments, exams, forum interactions, study notes	Digital input, OCR recognition	Analyze knowledge mastery and thought processes
Audio data	Classroom participation, group discussions, spoken Q&A	Microphone arrays, speech recognition	Assess verbal communication skills
Image data	Facial expressions, gestures, classroom behavior	Camera	Identify learning states and emotions
Video data	Classroom interactions, experimental procedures	Video recording, behavioral analysis	Assess practical skills and collaboration abilities
Log data	Online learning paths, resource clicks, interaction records	Log collection management system	Analyze learning strategies and interest preferences

Construct machine learning predictive models to analyze student academic performance patterns. For example: Utilize historical academic data (such as regular assignments and unit tests) to forecast final exam scores, enabling early warning for at-risk students.

Utilize sequence pattern mining to identify efficient and inefficient learning paths. Employ clustering analysis to segment students based on behavioral patterns, characterizing their learning habits, engagement levels, and strategy preferences. This provides a basis for guiding learning methods and determining intervention timing.

Leverage natural language processing (NLP) to analyze students' psychological and emotional modalities, gaining insights into their intrinsic needs, learning motivations, and emotional states. This enables care at the "affective computing" level.

Integrating all these analytical outcomes generates a dynamic, multidimensional student profile tag. This profile broadly encompasses:

(1) Knowledge state: Position on the knowledge map and distribution of strengths/weaknesses.

(2) Behavioral characteristics: Learning habits, engagement patterns, and strategy preferences.

(3) Psychological traits: Current emotional state, learning motivation, and encountered difficulties.

3.2.2. Fine-grained knowledge graph construction

Deconstruct course knowledge into granular knowledge points and establish semantic relationships such as prerequisites, dependencies, and associations between them. This creates a "knowledge map" for precise learning interventions, enabling interventions to trace back and navigate based on the logical structure of knowledge. Taking the "Data Mining" course as an example, the specific steps are:

(1) Granularization: Decompose a course into a hierarchical structure of "chapters—sections—knowledge points," ultimately arriving at "atomic knowledge points." For instance, within the "Apriori Algorithm" section of the "Association" chapter, "how to generate frequent item sets" itself can serve as an atomic knowledge point, while its derivation process can be another associated knowledge point.

(2) Attribute definition: Assign multidimensional attributes to each knowledge point, including: cognitive dimension, difficulty level, and importance level.

  (a) Cognitive dimension: This dimension defines the cognitive level students must achieve to master the knowledge point, ranging from lower-order to higher-order thinking. Examples include: understanding, memorizing, applying, and analyzing different concepts and techniques.

  (b) Difficulty level: This dimension classifies content points as elementary, intermediate, or advanced based on the concept's abstraction, mathematical foundation requirements, and implementation complexity.

  (c) Importance: This dimension categorizes knowledge points as core exam points, general knowledge, or extension content by considering curriculum requirements, whether they effectively supplement core knowledge, or their applicability in specific fields.

(3) Relationship establishment: Constructs knowledge point relationships within the curriculum. Includes:

  (a) Prerequisite relationship: Defined as "If A is not understood, then B cannot be discussed." For example, "Without understanding information theory (e.g., information entropy, information gain), decision trees (ID3 algorithm) cannot be discussed."

  (b) Dependency relationships: Defined as "Mastering A significantly enhances the learning process for B, leading to a deeper and more thorough understanding." For example, "Understanding logistic regression facilitates better comprehension of neural networks, as logistic regression can be viewed as a neural network without hidden layers. Grasping the former greatly aids understanding of the latter's activation functions and output layer."

(c) Associative relationship: "A and B embody similar principles, solve analogous problems, or can be used in combination." For example: "Classification and clustering are two major tasks in data mining, contrasting the fundamental difference between 'supervised learning' and 'unsupervised learning.'"

(d) Whole-part relationship: "A is a sub-step or component of B." For example: "Association rules, conceptually decomposed into support, confidence, and lift."

Once the knowledge graph is constructed, it is presented to teachers and students as a network diagram, making the knowledge structure immediately clear. When a student encounters difficulty with a specific knowledge point, the system can trace back along the "prerequisite relationship" to quickly identify the root cause of their weakness.

3.2.3. Fine-grained cognitive diagnosis of knowledge gaps

Large models utilize knowledge graphs and student profile tags as contextual information. The reasoning process is guided through prompt engineering. Taking the Data Mining course as an example, suppose "Student A achieved only a 40% accuracy rate on exercises related to a specific knowledge point. According to the knowledge graph, this topic heavily relies on 'two concepts.'" The large model infers that "The student's fundamental issue lies in insufficient understanding of two prerequisite concepts, preventing correct application of exercises in this topic. Immediate root-cause intervention is recommended." Specific steps:

(1) Problem identification: Student A has a 40% accuracy rate on exercises related to "decision tree pruning."

(2) Context injection:

(a) Input knowledge graph information, including the current problem's knowledge point, cognitive dimensions, prerequisite relationships, and dependencies.

(b) Input student profile tags, including academic tags, behavioral tags, and emotional tags.

(c) Diagnose root cause: Analyze the most probable fundamental reason for Student A's difficulty with "decision tree pruning."

(3) Large model reasoning output:

Through "surface analysis–root cause analysis–comprehensive assessment," it was determined that Student A's performance on this knowledge point heavily depends on understanding "model overfitting and generalization." Student profiling data confirms a "weakness" in this specific knowledge area. The root cause is not an inability to perform the "pruning" operation, but rather a lack of understanding of "why pruning is necessary"—specifically, an inadequate grasp of the core concept of "overfitting." Therefore, the conclusion is: Student A's fundamental issue lies in a superficial understanding of the prerequisite concept "model overfitting and generalization," failing to establish a deep connection between this concept and the practical application of "decision tree pruning."

The fine-grained cognitive diagnosis module for knowledge gaps achieves precise "etiological" localization of learning problems by deeply integrating structured knowledge graphs with dynamic student profile tags under the reasoning capabilities of large models. This lays a solid foundation for initiating efficient, personalized "treatment" plans.

3.2.4. Precision intervention based on natural semantics

Based on the diagnostic results above, the large model automatically generates a personalized intervention strategy for Student A: it strongly recommends that Student A relearn the "Model Overfitting and Generalization" module, designs targeted exercises, and provides encouraging emotional support and technical guidance when pushing learning resources. This precision intervention based on natural semantics transforms the "strategy" from the intelligent decision-making layer into executable "actions." Specific intervention methods include:

(1) Intelligent guided learniny integrating an intelligent Q&A system and contextual dialogue mechanisms, the system proactively explores students' knowledge structures, cognitive biases, and interest inclinations. For instance, AI tutors built on large language models can simulate Socratic questioning to engage students in sustained, deep conversations during new lesson previews. This approach not only activates prior knowledge but also sparks intrinsic motivation and anticipation by introducing cognitive dissonance or showcasing engaging real-world applications, transforming passive previewing into active knowledge discovery.

(2) Post-class personalized enhancement and assessmenhe system fundamentally transforms traditional one-size-fits-all homework assignments. Leveraging in-class performance data (e.g., responses, participation) and real-time knowledge mastery assessments, it automatically generates highly customized assignments. For students demonstrating strong mastery, the system primarily pushes comprehensive application and innovative exploration problems. For those with knowledge gaps, it focuses on concept comprehension and foundational reinforcement exercises. It dynamically adjusts subsequent problem types and difficulty based on homework completion, establishing a closed-loop learning process of "assessment-practice-reassessment."

(3) Dynamic course path planninhe system synthesizes curriculum standards with individual student characteristics to generate personalized knowledge acquisition trajectories and competency development curves. It recommends tailored learning content and pacing for each student, dynamically adjusting subsequent materials, sequence, and progress. Advanced learning themes are suggested for high-achieving students, while remedial review paths are mapped for those requiring support. This truly transforms teaching pacing from a one-size-fits-all approach to a personalized learning journey.

4. Conclusion and outlook

This paper systematically explores a large model-driven precision learning intervention model for university students, providing a comprehensive exposition across multiple dimensions, including multimodal data collection, course knowledge graph construction, student image tagging, and large model application. Through comprehensive perception and deep integration of multimodal data, coupled with the synergistic effects of knowledge graphs and large models, it enables a profound understanding of the learning process and precise intervention, delivering genuinely personalized learning support to university students. This research not only holds theoretical innovation value but also provides a feasible pathway for smart education practices. With continuous technological advancements and evolving educational philosophies, large model-driven precision learning interventions will play an increasingly vital role in enhancing higher education quality, ultimately achieving the organic integration of scaled education and personalized cultivation.

Disclosure statement

The authors declare no conflict of interest.

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