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A New Paradigm of Personalized Education Driven by Multi-Agent Collaboration

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Abstract: In order to promote the in-depth development of intelligent education, this paper proposes an intelligent collaboration framework that integrates general-purpose large language models and professional small models. By integrating the broad language comprehension ability of the general model and the fine grasp of subject knowledge of the domain-specific model, and combining the teaching mechanism in learning theory, the framework realizes a diversified knowledge construction method and supports a highly personalized and dynamically adaptive learning experience. We further explore the practical application scenarios of the framework in intelligent education, and demonstrate its potential in teaching assistance, learning guidance and knowledge transfer. With the continuous evolution of artificial intelligence technology, the collaborative system is expected to become a key engine to promote the intelligent transformation of education in the future.

Keywords: Multi-agent Collaboration, Fusion of Large Language Model and Small Model, Personalized Learning Experiences, Intelligent Transformation of Education.

Disciplines: Education. **Subjects:** Educational Technology.

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1 INTRODUCTION

Contemporary education is increasingly evolving toward personalized, precise, and seamless support, aiming to provide tailored learning solutions based on learners' cognitive states, interests, and individual characteristics. Over the past three decades, continuous breakthroughs in natural language processing (NLP) have significantly expanded the role of artificial intelligence in educational contexts, opening up new possibilities for creating more interactive, adaptive learning experiences and for developing intelligent, efficient educational tools and systems.

Among the foundational technologies enabling this transformation, the quality and structure of textual data processing play a critical role. In particular, the integration of lexical and semantic features in text preprocessing has proven effective in enhancing the accuracy and interpretability of downstream AI models. Hu, Niu, and Tang (2021) demonstrated this approach in the domain of fault text processing for metro signaling equipment, showing how fusing lexical domain and semantic domain information can lead to more nuanced and context-aware data representations [1]. These insights offer valuable methodological reference for the educational field, where similarly complex textual data—such as learner-generated content, course descriptions, and instructional materials—require high-quality preprocessing to support intelligent analysis and personalized recommendation.

2 RELATED WORK

2.1 LIGHTWEIGHT MODEL PRACTICE IN INTELLIGENT EDUCATION

Early educational technology systems mostly focused on the completion of a specific subject or a single task. For example, bag-of-word models were initially used for text classification tasks, while LSTM models were mostly used for scenarios such as language translation and question answering. At the same time, knowledge graphs (KGs) have also been introduced into education to support learning path recommendation and scientific research information retrieval. This kind of small, domain-focused model has been widely used in the field of educational technology because of its simple structure, high computational efficiency, and easy interpretation. They provide clear boundaries of knowledge for teachers to analyze and guide their learning process, especially in settings where resources or computing power are limited. However, these models have obvious bottlenecks at the functional level - due to the limitations of the training data and the structural limitations of the models themselves, they can only handle a narrow range of tasks, lack the ability to reason deeply and generate natural language, and therefore struggle to meet complex learning needs[2-4].

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2.2 Large Language Models Empower the Innovation Path of Intelligent Education

In recent years, the rapid development of large language models (LLMs) has injected new vitality into intelligent education. Models such as BERT and GPT demonstrate strong language understanding and generation capabilities through pre-training of massive corpora, and can achieve fluent natural language output, accurate question answering, and processing of multi-language-related tasks. The new generation of language models represented by ChatGPT further introduces human feedback reinforcement learning on the basis of pre-training, and optimizes the model response through human annotation, thereby improving the dialogue quality and task adaptability. This human-machine collaborative training mechanism not only makes the model more anthropomorphic, but also effectively avoids the generation of inappropriate content[5].

In education, the strong performance of LLMs has attracted a lot of attention, driving the rapid development of a variety of applications, including intelligent tutoring systems (ITSs), adaptive learning platforms, and virtual assistants for student needs. With its natural language understanding and generative advantages, ChatGPT-like models can provide learners with personalized explanations, question answers, and interactive learning content, creating a more immersive and adaptive learning environment. At the same time, the researchers also explored the integration of advanced technologies such as natural language processing and emotion recognition into teaching scenarios to dynamically perceive students' emotions and engagement, and then adjust teaching strategies and feedback in real time. While there are still challenges such as model controllability and ethical use, the trend of integrating LLMs into the education system is undoubtedly reshaping teaching and learning and opening up a wide range of opportunities for building highly personalized, interactive learning experiences. It is worth noting that the core of this paper is not to propose new large model structures or fine-tuning schemes, but to explore how to use the potential of existing large language models more effectively in real teaching scenarios[6-8].

2.3 The Role of Learner Style Modeling in Intelligent Education

Learners exhibit several opposing dimensions of preference in the way they process information: perceptual vs. intuitive, visual vs. verbal, active vs. reflective, and sequential vs. holistic. Active types tend to learn through practice and cooperation, while reflective types prefer independent thinking and introspection. Perceptual learners rely on concrete facts and real-world senses, while intuitive learners excel at abstract concepts and theoretical derivations. The visual type is good at extracting information from images and diagrams, while the verbal type is more suitable for learning through oral or written words. Sequential students are accustomed to understanding knowledge step by step, while holistic students are good at grasping the overall structure from the perspective of the whole picture.

Learners are divided into four styles: doers, reflectors, theorists, and practitioners. Actors tend to learn by doing and like new experiences; Reflectors pay more attention to observation and introspection, and analyze learning situations from multiple perspectives. Theorists favor logical reasoning and structured information; Practitioners, on the other hand, focus on practicality and real-world application scenarios. This model emphasizes the differences in the personality of different learning styles in the process of knowledge acquisition and processing, and is a powerful tool for developing differentiated teaching strategies[9].

Learning is a dynamic cyclical process that encompasses four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation. Learners gain experience through practice, reflect on the experience, summarize concepts or principles, and finally apply these theories to new practice. Such cycles not only strengthen knowledge acquisition, but also help to build deeper cognitive understanding and skill application.

There are four types of learning preferences: visual, auditory, literate and kinesthetic. Visual students are better at obtaining information through visual elements such as diagrams and charts; The auditory type prefers to learn through listening to lectures, discussions, and other forms of speech; Literacy tends to acquire knowledge by writing and reading texts; Kinesthetic, on the other hand, is more suitable for learning through hands-on activities, simulations, or real-world experiences. This model provides clear guidance for multimodal teaching and learning, which can help the education system to better meet the perceived preferences of different learners[10].

2.4 Discussion on the Advantages and Disadvantages of Large Language Models and Specific Models from the Perspective of Model Collaboration Depth of Expertise

Although large language models (LLMs) perform well in general tasks, their ability to train corpora in specific disciplines is often limited by the breadth and lack of specialization of training corpus. For example, tasks such as chemical equation generation require high knowledge accuracy and logical consistency, while LLMs often struggle to master such highly structured, rule-dependent knowledge. In contrast, domain-specific models (DSMs) can be fine-tuned for a certain professional domain, which is easier to capture the key concepts and implicit logic in the discipline, and has stronger task adaptability[11].

DSMs usually have a fixed output format, such as the triplet form in the knowledge graph, which makes them more suitable for the transfer of structured data; LLMs, on the other hand, use reinforcement learning and human feedback (e.g., RLHF) to continuously optimize the output, making the generated content more human-like in terms of expression and value alignment. As a result, LLMs are able to output language that is more natural and in line with students' cognitive styles, easier to understand and accept, and more likely to embody educational ethics such as respect and fairness. This characteristic is particularly important in educational scenarios that emphasize humanistic care.

LLMs have a wide range of knowledge coverage, which gives them a clear advantage when dealing with open-ended, cross-domain problems, especially in zero-shot learning or complex reasoning tasks. However, the blurred boundaries of knowledge also bring new problems: the model may generate information that is irrelevant to the learning goal, interfere with students' attention, or output content beyond their comprehension, affecting learning outcomes. In contrast, the knowledge scope of DSMs is more concentrated, which helps teachers and systems to better control the depth and breadth of content, and ensure the pertinence and controllability of teaching[12].

Since the knowledge of LLMs mainly comes from the pre-training stage, the update cycle is long and the cost is high, which makes them easy to become "outdated" in the face of the field of rapid knowledge update. For example, finance, technology, or policy-related courses can change significantly in a short period of time, and LLMs often struggle to respond in a timely manner. In contrast, DSMs are especially suitable for dynamically changing teaching scenarios due to their smaller model size and higher update efficiency, which can quickly adapt to emerging content and maintain the freshness and relevance of knowledge.

LLMs and DSMs have their own advantages and limitations. LLMs are more capable of language generation and open reasoning, while DSMs excel in professional knowledge and rapid iteration. With the complementary characteristics of the two in terms of knowledge type and technology structure, supplemented by the guidance of human insight, it can lay a solid foundation for building a more intelligent education system. From this perspective, the collaborative model architecture for multi-dimensional educational tasks such as learning, teaching, and decision-making may become the key direction for the development of intelligent education in the future[13-14].

3 LDMC COLLABORATIVE ARCHITECTURE IN INTELLIGENT EDUCATION

3.1 FRAMEWORK STRUCTURE AND MODEL SYNERGY MECHANISM

The architecture design of LDMC integrates the capability boundaries of different models, and provides all-round support for educational tasks with the help of multiple knowledge representation technology (MKR). The general-purpose large model provides a wide range of interdisciplinary knowledge backgrounds, enabling the system to flexibly understand diverse teaching topics. The professional small model accurately models and expresses the core concepts in a specific domain to ensure the accuracy of knowledge and contextual adaptation. At the same time, the learning theory model injects teaching strategies and style control mechanisms to make the framework have the ability to respond to individual differences and promote the teaching process to be more adaptive and personalized[15].

3.2 DYNAMIC ADAPTATION MECHANISM DRIVEN BY INDIVIDUALIZATION

One of the most notable features of LDMC (Learner Driven Memory Controller) is its ability to dynamically respond to individual learner characteristics, making it a powerful tool in the field of personalized education. Traditional education systems often rely on fixed teaching models and static course content that fail to fully account for the diversity of learners' cognitive styles, preferences, and learning progress. In contrast, LDMC uses advanced computing techniques to make real-time adjustments to ensure that the learning experience remains highly relevant and effective for each student.

At the core of LDMC's adaptive capabilities lies an advanced mechanism that continuously updates the memory state of students' learning styles. The system collects and analyzes behavioral data during the learning process - including interaction frequency, task completion time, response accuracy, and engagement metrics - to assess learners' current cognitive and emotional states. In this way, LDMC can identify subtle changes in learning behavior and immediately adjust teaching strategies to better adapt to learners' changing needs.

Specifically, LDMC uses a reward-based evaluation mechanism to assess learners' current learning progress and engagement. Based on real-time feedback, the system dynamically recalculates and updates the weighted combination of various learning style models (LSMs). These models represent different cognitive traits, such as visual, auditory, kinesthetic, or analytical learning preferences. By adjusting the balance between these models, LDMC ensures that the teaching method is always in line with the learner's

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main and emerging traits.

This process is achieved by using gradient backpropagation in a reinforcement learning framework. Unlike static machine learning models, reinforcement learning allows LDMC to learn from a continuous stream of interactions and gradually improve its predictive accuracy and personalization capabilities over time. Each learner's input is a kind of environmental feedback that the system uses to optimize its internal parameters. As a result, the LDMC model evolves based on long-term trends and instantaneous changes in learner behavior, gradually approaching the optimal state of personality adaptation.

Thanks to this self-optimization mechanism, LDMC not only achieves high personalization, but also enhances the system's ability to detect and respond to learners' development trajectories. For example, if a student shows signs of cognitive fatigue or a decline in learning motivation, the system can reduce cognitive load by simplifying the task structure or introducing engaging multimedia content. Conversely, if the system detects that the student's engagement and understanding are high, it can increase the difficulty of the task or introduce more challenging concepts to maintain an optimal learning flow[16].

Furthermore, LDMC's adaptability extends beyond content delivery to interactive formats and teaching strategies. It can switch between different interactive modes, such as quizzes, simulations, storytelling, or problem-based learning, based on the most effective interaction mode for an individual at any given moment. This fine-grained responsiveness significantly increases student engagement, allowing them to feel cared for, understood, and supported in their learning process.

As students progress, LDMC builds an evolving learner profile, like a dynamic memory bank that records not only what students learn, but also how they learn. This enables long-term personalization, with the system able to anticipate needs and adapt in advance to future learning challenges. In this way, LDMC creates a deeply immersive, intelligent learning experience that evolves as learners progress and creates a sense of continuity and coherence in their learning path.

Ultimately, LDMC represents a major advancement in the convergence of artificial intelligence and education. By integrating real-time data analysis, reinforcement learning, and psychological modeling, it paints a blueprint for the future of truly learner-centric systems. Its ability to personalize instruction, adapt content, and support diverse learner profiles makes it a cornerstone technology for the next generation of intelligent tutoring systems.

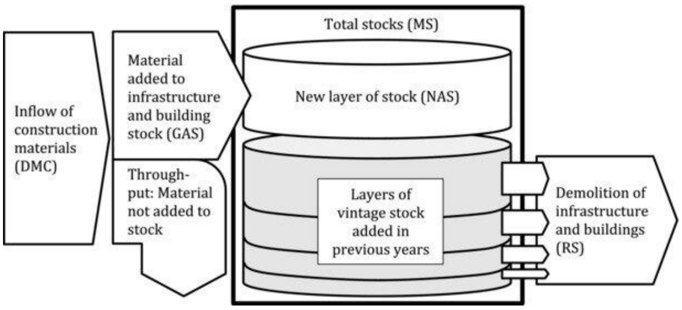

FIG. 1 LDMC FRAMEWORK.

3.3 Model collaboration mechanism: Triple fusion path of LLMs and DSMs

In order to achieve more efficient educational intelligence, this paper proposes three typical collaboration modes between LLMs and DSMs: knowledge injection, knowledge supplementation, and knowledge constraint.

In the knowledge injection mode, DSMs are embedded in LLMs as lightweight modules to improve their ability to perceive and generate professional content. This can be done by freezing most of the LLM's parameters and fine-tuning only the task-relevant adaptation layers, such as task-specific insertion modules or prompt designs. In addition, LoRa technology significantly enhances the context adaptability and semantic alignment ability of LLMs by introducing a low-rank adjustment strategy to efficiently inject subject knowledge with lower computing resources.[17]

In the knowledge supplement mode, DSMs, as an external knowledge module, support LLMs to deal with professional problems, making up for their shortcomings in structured understanding and factual accuracy. Taking Knowledge Graphs (KGs) as an example, the system can parse natural language queries into semantically aligned subgraphs, and then translate the triples in the subgraphs into linguistically fluent responses. In this way, it not only enhances the interpretability and accuracy of answers, but also reduces the risk of hallucinations in language models, providing a solid information foundation for complex and higher-order learning tasks.

In the knowledge constraint mode, the system screens the LLMs output in real time through the external domain model to ensure that the content conforms to the subject knowledge boundary. Operationally, target domains such as mathematics, history, or physics are defined and a specialized domain discriminator is trained to evaluate the results generated by LLMs. If an output deviates from the domain specification, the system uses DSM's structured knowledge to make a correction. This process can be optimized in combination with the RLHF mechanism, and the model boundary rules can be dynamically adjusted through human feedback, so as to achieve a balance between generative flexibility and academic rigor, and provide a guarantee for a focused learning experience.

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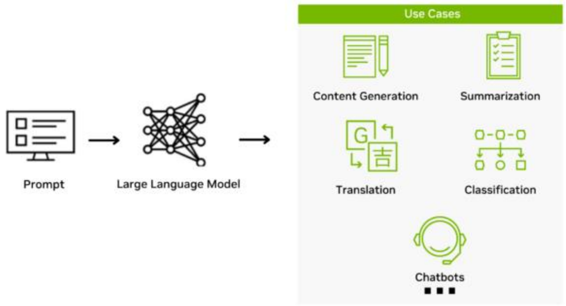

FIGURE 2 COLLABORATION PATTERNS FOR LARGE LANGUAGE MODELS (LLMS) AND DOMAIN-SPECIFIC MODELS (DSMS).

4 APPLY PRACTICAL SCENARIOS

4.1 COLLABORATIVE LEARNING SUPPORT

Group learning, also known as collaborative or cooperative learning, is a teaching method that emphasizes collective goals and interactive participation. It considers learning to be a highly social process, emphasizing the ability of students to communicate, collaborate and build knowledge together. Its core elements include:

Collaboration: Through task sharing and mutual support, students can establish an effective communication mechanism and promote the common development of each other's cognition.

Initiative: Learners become active constructors of knowledge by actively participating in discussions, debates, and problem solving[18].

Feedback: Through peer assessment and self-reflection, students continuously correct cognitive biases and improve their learning strategies and critical thinking skills.

In this teaching mode, LDMC provides stable and dynamic technical support for the group collaboration process:

To prevent the group from diversifying their perspectives from the core goal, LLMs keep track of the discussion, while the DSM ensures that the content aligns with disciplinary boundaries and keeps the discussion on track.

LDMC can analyze semantic interaction activity to determine whether communication is ineffective. If a team energy drop is identified, DSMs can step in to provide incentives, while LLMs can ask questions or throw out key clues to reactivate the discussion.

The framework also tracks each member's learning trajectory, monitors progress differences, and automatically assigns appropriate assists to ensure that each learner is on the same page in a collaborative environment.

4.2 PERSONALIZED INTELLIGENT TUTORING SYSTEM

Individualized Teaching System (ITS) has long been recognized as one of the important paths for educational technology change. With LDMC, intelligent tutoring is no longer driven by a single algorithm, but realizes in-depth adaptation to learners' needs through model collaboration.

LDMC dynamically adapts instruction to students' interests, abilities, and goals, providing an immersive, interactive tutoring experience for tasks such as solving math problems, explaining abstract concepts, or guiding language expression. Its key advantages include:

Personalized supportBy analyzing learning behavior and feedback, LDMC adjusts the difficulty of suggestions and exercises in real time, matches learning style and rhythm, and builds individualized learning paths.

The multi-platform accessibility system can be embedded in various platforms such as web pages, apps, and chatbots to expand learning scenarios and enhance the convenience of resource acquisition.

Learning Enablement LLMs provide continuous language interaction and encouragement, and DSMs track knowledge acquisition status, forming a "lifelong learning coach" that supports students in optimizing their goals and strategies over the long term.

Reflection and assessment support students can use the system to self-assess learning outcomes, identify weak areas, adjust learning strategies, and achieve self-regulation of the learning process.

4.3 OPTIMIZATION OF TEACHING MANAGEMENT

In the modern educational environment, classroom management is becoming more and more important as one of the key factors for the smooth progress of teaching. With the increasing diversification of teaching modes and the development of digitalization, teachers are faced with more and more complex teaching situations and students' differentiated needs, and traditional management methods are difficult to fully meet the current teaching requirements. Therefore, how to optimize teaching management through technical means has become an important topic in the process of education reform and informatization. To this end, LDMC (Learning Design & Management Companion), an intelligent teaching management platform based on large language models (LLMs) and domain-specific models (DSMs), came into being, aiming to provide teachers with a whole-process support system from rule setting to evaluation feedback[19].

In terms of classroom management, LDMC provides a personalized and structured suggestion generation mechanism. Teachers can interact with the system through natural language, input students' individual characteristics (such as learning ability, behavioral habits, emotional state,

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etc.), course type and specific teaching goals, and the system will automatically generate multi-dimensional management suggestions covering discipline management, classroom participation, teacher-student interaction, group cooperation and other dimensions. For example, for classes with poor discipline, the system can recommend setting clear behavior norms and incentive mechanisms; For classes with obvious stratification of learning ability, teachers are advised to adopt differentiated grouping strategies to improve overall classroom efficiency and student motivation. This highly personalized management support not only reduces the burden on teachers, but also improves the responsiveness and flexibility of classroom teaching.

In the evaluation and feedback process, LDMC realizes automatic homework correction and feedback template generation based on large language models. After the teacher completes the assignment, the system can automatically score according to the students' answers and generate personalized comment content, which not only covers the mastery of knowledge points, but also puts forward suggestions for improvement, which is highly targeted and practical. At the same time, the domain-specific model provides professional discipline evaluation criteria, making the evaluation process more scientific and accurate. For example, in mathematics, DSM is able to identify the completeness and logical rigor of the problem-solving steps; In the writing course, you can analyze multiple dimensions such as language expression, structural arrangement, and depth of argumentation. This combination of "intelligence + professionalism" assessment mode greatly improves the quality and timeliness of teaching feedback, helps students find problems faster and improves learning methods[20-22].

As an important part of teaching management, curriculum design is directly related to the integrity of teaching content, the rationality of the rhythm and the richness of resources. In this regard, LDMC provides systematic curriculum design support to teachers. Teachers only need to input the teaching objectives and syllabus, and the LLM can generate a logical, well-organized teaching framework, and suggest language expressions to make the course content more organized and understandable. DSM further complements subject expertise, a library of case resources, and a wealth of interactive teaching activity suggestions, providing teachers with in-depth content expansion and practical suggestions. For example, when a history teacher is teaching about an event, DSM can provide real historical archives or case simulations to enhance students' immersion and critical thinking skills. Overall, this intelligent curriculum planning system has significantly improved the efficiency and quality of teachers' lesson preparation, and promoted the teaching activities from "experience-led" to "data-driven and intelligent support".

LDMC provides strong technical support for all aspects of teaching management by integrating large language models and domain-specific models. From classroom management, assessment feedback to curriculum design, the system can achieve a high degree of automation and personalization, helping teachers complete teaching tasks more calmly and efficiently in a complex and changing teaching environment. This new mode of teaching management optimization indicates that education informatization has entered a new era of intelligent collaboration, which not only improves teachers' professional practice ability, but also creates a more orderly, efficient and personalized learning environment for students[23-28].

4.4 Empirical evidence from user research

To validate LDMC's performance in real-world teaching scenarios, we designed and conducted a user study with 30 students tasked with collaborating on a programming project. In the experiment, three sets of systems were set up: the traditional LLM system, the LDMC version without learning style modeling, and the complete LDMC system, which played the roles of mentor, collaborator and motivator in the task, respectively[29-33].

After the task is completed, students rate the performance of the system, and the evaluation dimensions include the accuracy, relevance and positive support perception of the content. The scores were scored using a binary method (1 for satisfaction and 0 for dissatisfaction), and the statistical results are shown in Table 1. The data show that the complete LDMC framework performs best in improving the quality of group collaboration, guiding direction and maintaining interaction, which preliminarily verifies the effectiveness of the multi-model collaboration mechanism in actual learning[33-37].

Through the in-depth discussion of the above application scenarios, we can clearly see that the LDMC framework not only has the advantages of multi-model integration in theory, but also shows a high degree of adaptability and practicability in practical teaching situations. Whether it's facilitating team coordination in collaborative learning, providing differentiated tutoring for individual learners, or optimizing classroom management and improving the efficiency of instructional design, LDMC has injected new intelligence into educational practice. At the same time, the user research results also preliminarily verify the effectiveness and feasibility of the framework in real teaching tasks, and provide a solid foundation for its further promotion and application. Based on this, the next chapter will focus on the implementation strategy, system deployment process, and practical challenges of the framework, so as to further improve the sustainable implementation path of LDMC in the education scenario[38-39].

5 SUMMARY AND OUTLOOK

In this paper, LDMC, a collaborative model framework for intelligent education scenarios, is proposed and systematically expounded. The framework integrates the advantages of large language models (LLMs), domain-specific models (DSMs) and learning theory models, and constructs a multi-level, multi-perspective, multi-source fusion model collaboration mechanism. Through deep interaction and complementarity between models, LDMC is able to generate multiple knowledge representations (MKRs) to drive the evolution of educational experiences in a more personalized, adaptive, and intelligent direction.

At the specific application level, this paper explores the functions and performance of LDMC in multiple key scenarios such as group learning, personalized tutoring, and instructional management, and demonstrates the broad potential of the framework to support complex teaching tasks, optimize the learning process, and improve student engagement. Furthermore, empirical research verifies its effectiveness in collaborative learning, which provides a practical basis for its deployment in the real educational environment.

To sum up, LDMC not only represents an advanced educational assistance system, but also demonstrates a new paradigm of educational technology with collaborative intelligence as the core. With the continuous evolution of artificial intelligence and educational technology, LDMC is expected to provide structural support for the future intelligent teaching system, become an important engine to promote educational reform, and provide a solid foundation and continuous impetus for the development of personalized learning and lifelong learning.

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DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

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