

Reform and Practice of an AI-Driven Discrete Mathematics Teaching Model from the Perspective of the OBE Concept

Fujiao Ju, Shaotao Zhu*

College of Computer Science, Beijing University of Technology, Pingle Yuan 100, Chaoyang District, Beijing, China

**Author to whom correspondence should be addressed.*

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Abstract: As a core foundational course for computer-related disciplines, reforming the teaching model of Discrete Mathematics is critically important. Driven by the Outcomes-Based Education (OBE) concept and the national “Artificial Intelligence (AI) + Education” strategy, there is a compelling need to transform traditional pedagogical approaches towards data-intelligence. Leveraging the OBE framework and AI technologies, this study focuses on the teaching reform of Discrete Mathematics. It constructs a “Data-Driven–Cognitive Computing–Precise Intervention” theoretical framework and establishes three progressive objectives: (1) developing an AI-assisted integrated framework for “learning-oriented teaching”; (2) designing personalized teaching strategies; and (3) innovating precision intervention models. The research specifically addresses four key issues: dynamic analysis of learning states, generation of personalized strategies, human-computer collaborative mechanisms, and an effect evaluation system. Empirical evidence demonstrates that the proposed AI-driven OBE teaching model significantly enhances instructional precision, improves student competency outcomes, and promotes the achievement of course objectives. This study provides substantial theoretical and practical support for the digital transformation of Discrete Mathematics instruction and the broader intelligent teaching reform initiative in higher education.

Keywords: OBE concept; AI-driven; Discrete mathematics; Intelligent teaching; Multimodal learning

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1. Introduction

Discrete mathematics, as a core foundational course for majors such as Computer Science and Technology, Big Data, and Artificial Intelligence, directly influences the cultivation of students’ abstract thinking, logical reasoning, and problem-modeling abilities. It is the theoretical cornerstone for subsequent courses like Data Structures, Algorithm Analysis, and Artificial Intelligence ^[1]. Since 1977, the IEEE has designated it a core course for computer-related majors, emphasizing its irreplaceable role in analyzing discrete quantity structures and modeling systems ^[2]. However, the current teaching of discrete mathematics faces multiple

challenges: firstly, teaching models are often rigid, dominated by theoretical lectures that lack integration with engineering practices, leading to a disconnect where students “learn but cannot apply”^[3]. secondly, assessment methods are monolithic, over-relying on final closed-book exams while neglecting formative process-oriented evaluations, making it difficult to comprehensively assess student competency outcomes^[4]. thirdly, the prominent contradiction between course content and class hours—due to dense abstract concepts and strong logicity, traditional teaching struggles to balance depth and breadth, resulting in low student interest in learning^[5].

With the advancement of professional engineering education accreditation and the deepening of the “AI + Education” strategy, the educational philosophy is transforming from “knowledge transmission” to “outcome orientation”^[6]. Outcome-Based Education (OBE) emphasizes student competency outcomes as its core, achieving continuous improvement by dynamically adjusting teaching objectives and evaluation systems. Engineering accreditation requires courses to align closely with graduation requirements and cultivate students’ capacity to solve complex engineering problems. In this context, the reform of discrete mathematics teaching needs to address three demands: firstly, how to integrate abstract theories with professional practices in computer science to strengthen the course’s relevance to subsequent studies; secondly, how to leverage information technology to break through the limitations of traditional teaching and realize personalized learning and precise intervention; thirdly, how to construct a diversified evaluation system to ensure the consistency between the teaching process and student learning outcome objectives.

Existing studies have conducted active explorations: some scholars have optimized teaching content and assessment methods based on the OBE concept, and improved classroom interaction through blended learning^[2]. other studies have introduced technologies such as knowledge graphs and digital twins to attempt to structure and visualize teaching resources^[7]. there are also practices that combine discrete mathematics with big data and artificial intelligence case studies to enhance the course’s practical applicability^[8]. However, in general, existing reforms mostly focus on a single link (such as teaching methods or evaluation systems), lacking a systematic integration of “concept-technology-practice.” In particular, research gaps remain in AI-driven dynamic analysis of learning situations and the generation of personalized strategies.

2. Research content, objectives

2.1. Research content

Under the in-depth guidance of the OBE concept, this study employs artificial intelligence as the central driver to propose a groundbreaking teaching framework: “Data-Driven–Cognitive Computing–Precise Intervention.” This framework facilitates a fundamental shift in discrete mathematics education from empiricist paradigms to data-intelligence paradigms.

Theoretically, this framework innovatively integrates multimodal learning analytics, knowledge graphs, and cognitive diagnosis models into a logically rigorous three-layer architecture: The bottom layer relies on IoT sensing devices and intelligent terminals to capture real-time multi-dimensional data of students in discrete mathematics learning, including learning behavior data such as classroom answer speed and formula derivation trajectory, emotional data such as concentration and mood fluctuations collected via cameras and voice recognition, and cognitive state data reflected through phased tests and problem-solving processes, forming a comprehensive original data pool. The middle layer introduces large model technology to deeply process the multimodal data collected from the bottom layer. It explores the implicit connections between

behavior, emotion, and cognition through cross-modal feature fusion algorithms and dynamically generates learner profiles that encompass dimensions like knowledge mastery, cognitive weaknesses, and learning styles. For example, in the chapter “Graph Theory,” it can accurately identify the common logical faults of students in applying the shortest path algorithm. The top layer, guided by the competency outcomes defined by the OBE concept, generates interpretable instructional intervention strategies based on the learner profiles. For instance, it pushes targeted propositional calculus exercises to students with insufficient logical reasoning ability, and matches engineering case analyses for students with weak application ability, forming a complete closed loop of “perception-analysis-intervention-feedback” to ensure that each teaching link is closely centered on student competency goals.

Practically, a “three-stage progressive” implementation path is established: Firstly, systematically sort out the core concept system of discrete mathematics, including five modules: set theory, mathematical logic, algebraic structures, combinatorics, and graph theory. A knowledge graph containing core concepts and association rules is built through knowledge ontology modeling technology. This not only realizes the structured presentation of teaching content but also endows abstract mathematical knowledge with computability through the assignment of logical weights between concepts, providing precise content navigation for personalized instruction. Secondly, a multi-source data collection network is built upon a smart teaching platform, which real-time aggregates data such as bullet screen questions in classroom interactions, distribution of wrong options in online quizzes, formula editing trajectories in homework, and facial micro-expressions analyzed by the emotion computing model. Leveraging the deep learning capabilities of large models, a unique learning path map is generated for each student. For example, for students with a solid foundation in mathematical logic but weak application in graph theory, the system automatically recommends transitional learning resources from “logical reasoning to graph theory modeling,” and the difficulty of exercises and explanation methods are dynamically adjusted. Finally, digital twin technology is innovatively introduced into the teaching scenario. A virtual mirror of the discrete mathematics teaching process is built based on historical data, which real-time maps key indicators such as classroom teaching progress and students’ knowledge mastery curves. Predictive algorithms are used to simulate learning effects under different teaching strategies, such as early warning of possible understanding bottlenecks in a certain chapter, to assist teachers in dynamically optimizing teaching plans.

This integrated “theoretical framework–technical architecture–implementation pathway” establishes not only an actionable intelligent reform solution for discrete mathematics pedagogy but also extends a transferable model for foundational course innovation and talent development enhancement within higher education’s digital transformation.

2.2. Research objectives

With the OBE concept as the core value orientation and AI as the technical means, three progressive objectives are established for the discrete mathematics teaching mode:

First, construct an AI-assisted integrated framework of “teaching based on learning.” Through learner profiling and intelligent modeling of teaching scenarios, establish a data-driven, precise teaching decision model, reveal the enabling mechanism of AI in learning situation diagnosis, resource matching, and strategy optimization, and provide systematic theoretical support for intelligent education.

Second, develop AI-driven personalized teaching strategies. Design a teaching decision center integrating multimodal data perception, adaptive algorithms, and interpretable engines, and develop a

closed-loop teaching strategy of “monitoring-analysis-recommendation-feedback” to realize the intelligent transformation from whole-class instruction to personalized guidance, significantly improving teaching precision and adaptability.

Third, innovate AI-empowered, precise teaching modes. Construct a complete implementation path of “data collection-intelligent analysis-strategy generation-dynamic adjustment-effect evaluation,” form an operable technical framework and practical paradigm for large-scale individualized instruction, and verify its effectiveness, sustainability, and promotion value through cross-campus empirical studies.

3. Reform program design and problem-solving approaches

3.1. Constructing an AI-empowered theoretical model of “teaching based on learning”

The three-element theoretical framework of “cognition-emotion-society” in education is deeply integrated with the logic of machine learning algorithms, and a three-layer dynamic model of “data-driven–cognitive computing–precise intervention” is proposed. The bottom layer centers on learner profiles, realizing real-time portrayal of cognitive states through knowledge graphs and multimodal behavior data; the middle layer relies on generative large models to dynamically predict needs, and automatically matches personalized cognitive scaffolding in combination with the zone of proximal development theory; the top layer generates real-time teaching strategies under the constraints of interpretable rules, completing the paradigm leap from “teacher’s subjective presupposition” to “AI dynamic adaptation.” This model not only reveals the enabling mechanism of AI in learning situation diagnosis, resource matching, and strategy optimization, but also provides a verifiable and iterable algorithmic expression for the concept of “teaching based on learning.”

3.2. Designing an intelligent analysis strategy for multimodal learning situations

Centered on the “monitoring-analysis-recommendation-feedback” closed loop, this strategy integrates three technical engines—text semantic mining, knowledge graph tracking, and cognitive time-series analysis—to perform real-time fusion and in-depth parsing of multi-source heterogeneous data, including classroom voice, online interactions, answer trajectories, and emotional signals. Through a distributed “1+N” agent architecture, perception small models are responsible for lightweight tasks such as audio-video-to-text conversion and emotion recognition, while cognitive large models complete cross-modal feature fusion, learner long-term memory modeling, and personalized path generation. This strategy maps group teaching strategies to individual learning paths, realizing the leap of teaching content from “static presupposition” to “dynamic generation.” Meanwhile, it provides teachers with an interpretable decision-making dashboard to ensure that teaching intelligence is both precise and controllable.

3.3. Designing a teaching mechanism with a dynamic closed-loop and resource adaptation

Following the logical thread of “data-driven–strategy optimization–effect feedback,” a self-evolving closed-loop for teaching governance is constructed. First, relying on smart classroom pens, online platforms, and edge computing devices, students’ learning behaviors, cognitive states, and emotional responses are sampled to form high-density cognitive time-series data streams. Subsequently, reinforcement learning algorithms are used to perform micro-decomposition and integral reconstruction of these data, updating learner profiles and class norms in real-time, which in turn drives the “N-step updates” and “prioritized experience replay” of teaching strategies. Second, a retrospective analysis dashboard for teaching decisions is designed, incorporating interpretable machine learning attribution models to help teachers intuitively grasp

the causal chain between “strategies and outcomes,” enabling dynamic fine-tuning and precise intervention of strategies. Finally, an evidence-based evaluation framework is established covering five dimensions: “knowledge mastery, depth of thinking, interaction quality, learning efficiency, and learning diversity.” Simulate and preview the intervention effects through the digital twin classroom to ensure that each strategy iteration is based on credible evidence. This mechanism not only achieves “real-time correction by AI, real-time intervention by teachers, and real-time adaptation of resources” but also provides a sustainable and replicable technical foundation for large-scale individualized teaching.

4. Innovation and feasibility analysis of teaching reform

4.1. Innovation of teaching reform

Constructing an AI-empowered theoretical model of “teaching based on learning”: By deeply coupling the cognitive laws of pedagogy with the logic of machine learning algorithms, a three-layer theoretical framework based on learner profile modeling, dynamic demand prediction, and teaching strategy generation is proposed. By revealing the enabling mechanism of AI technology in learning situation diagnosis, resource matching, and strategy optimization, it promotes the paradigm shift of precise teaching from “teachers’ subjective presupposition” to “AI dynamic adaptation,” realizes the algorithmic upgrading of the “teaching based on learning” concept, and provides interpretable and operable theoretical support for intelligent education.

Designing an intelligent analysis strategy for multimodal learning situations: Integrate text semantic mining, knowledge graph tracking, and cognitive time-series analysis technologies to develop an intelligent analysis system for multimodal learning situations. Through multi-dimensional data fusion, a dynamic learning situation diagnosis system is constructed to tackle the problems of fusing and real-time parsing unstructured data in teaching scenarios. An intelligent teaching engine is designed to support the closed-loop operation of the entire “monitoring-analysis-recommendation-feedback” process, enabling the dynamic mapping from group teaching strategies to personalized learning paths, enhancing the accuracy and real-time response capability of the teaching system, and promoting the leap of teaching intelligence from “static presupposition” to “dynamic generation.”

Designing a teaching mechanism with dynamic closed-loop and resource adaptation: Construct a dynamic optimization algorithm for teaching strategies based on cognitive time-series data to achieve precise intervention in hierarchical teaching. Develop a teaching decision retrospective analysis dashboard and reveal the causal relationship between teaching strategies and student development through machine learning attribution algorithms. Innovate the teaching quality evaluation model, establish an effective evaluation index system, and form a sustainable improvement mechanism of “data-driven iteration and AI real-time correction.”

4.2. Feasibility analysis

The concept of “teaching based on learning” is highly consistent with the orientation of current educational policies. National policies explicitly encourage the use of AI technology to carry out learning situation analysis and build a new intelligent teaching and learning model featuring “teaching based on learning—individualized teaching—promoting teaching through evaluation.” The policy level provides strong support for the implementation of “teaching based on learning.” “Teaching based on learning” can meet students’ personalized needs. By establishing a tutorial service center and a modular curriculum system, it provides

students with differentiated and personalized learning strategies, which are conducive to tapping into students' potential.

AI technology can accurately assess students' learning styles, interests, and abilities through intelligent algorithms and big data analysis, and tailor learning plans and resources for students. Personalized learning paths and real-time feedback mechanisms significantly enhance students' autonomous learning and interdisciplinary collaboration skills. AI's automated assessment and feedback can enhance the efficiency and accuracy of evaluation. In addition, AI can integrate and create diverse teaching resources to meet the learning needs of different students.

5. Conclusion

This paper systematically investigates an AI-driven reform of discrete mathematics pedagogy under the OBE paradigm, achieving a transformative shift from traditional instruction to intelligent precision teaching through integrated theoretical modeling, strategic design, and mechanism development. We construct the three-tier “Data-Driven→Cognitive Computing→Precise Intervention” framework, design multimodal learning analytics strategies, and establish the closed-loop “Data Collection→Intelligent Analysis→Strategy Generation→Dynamic Adjustment→Outcome Evaluation” instructional mechanism. This integrated approach provides algorithmic foundations for learning-centered pedagogy, shifts instructional decision-making from teacher presumption to AI-adaptive dynamism, and fulfills OBE's sustainable improvement goals through student-centered, outcome-oriented education.

Disclosure statement

The authors declare no conflict of interest.

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