AIGC Empowers Theoretical Teaching Visualization and Scaffold Construction

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Abstract. Multimedia Technology, a core theoretical course for digital media majors, is increasingly challenged by rapid technology iteration and the abstract nature of mathematically intensive content. While industry standards update within months, textbooks and classroom cases often lag by years, leading students to perceive what they learn as outdated and to rely on rote memorization that transfers poorly to authentic problem solving. This paper proposes an AIGC-empowered reform framework that reconfigures pure theoretical teaching through three mechanisms: concretization of symbolic systems (transforming formulas into manipulable multimodal representations), visualization of logical chains (supporting dynamic reasoning via interactive simulations and counterfactual demonstrations), and stratification of cognitive scaffolds (providing adaptive support aligned with learners' zone of proximal development). Based on these mechanisms, we construct a three-stage teaching model—theoretical visualization, logical concretization, and cognitive systematization—implemented through problem-driven preparation, interactive concept presentation, and collaborative verification and exploration. The approach further integrates AI-assisted lesson planning, a dual-teacher classroom in which instructors lead instructional logic while AI addresses personalized questions in real time, and a dynamic evaluation system that generates cognitive diagnosis reports from interaction data. Empirical results indicate improvements in conceptual accuracy, logical reasoning, and learning engagement, demonstrating AIGC's value as a "cognitive translator" that shifts instruction from symbolic memorization to meaning construction.

Keywords: AIGC, Multimedia theory teaching, Concretization, Cognitive scaffolding, Teaching reconstruction

1 Introduction

As a core theoretical course for digital media majors, Multimedia Technology faces teaching challenges with distinct characteristics of the times and disciplinary specificity. In an era where the technology iteration cycle has shortened to 18 months (Gartner, 2024), the course confronts dual challenges: the lag in knowledge updates and the effectiveness of theoretical teaching. These challenges manifest as follows:

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The Dilemma of Knowledge Lag: Generational Gap Between Technological Evolution and Textbook Updates. The curriculum system has long relied on traditional knowledge frameworks, with 20th-century standards such as JPEG and MPEG-2 still accounting for over 60% of teaching content. Industry data shows that the update cycle for multimedia technology standards has shortened to 11.8 months (the H.266/VVC standard was developed in just 22 months), while the update cycle for existing textbooks remains 3–5 years. This time lag leads to inaccurate case studies; for example, a textbook planned by a ministry still uses MPEG-2 (1995) as a video compression example, while the industry has widely adopted AV1 (2018) and H.266 (2020) standards. The temporal gap between knowledge supply and demand causes 38.7% of students to perceive a cognitive mismatch, viewing "what is learned in class as technological legacy." Emerging technologies such as AIGC-generated multimodal content compression and neural rendering are absent from textbooks, creating a 5–8-year generational gap between students' knowledge systems and industry needs.

Abstractness of Knowledge Representation: Disconnect Between Mathematical Symbols and Cognitive Structures. The course involves extensive mathematically intensive theories, such as DCT transformation matrix operations and the recursive construction of Huffman coding trees. Traditional blackboard teaching struggles to present dynamic derivation processes.

Cognitive Transformation Barriers: Disruption from Mechanical Memorization to Meaning Construction. In traditional teaching, 63% of students memorize formulas by rote to pass exams, but in real-world problem scenarios, only 19% can correctly apply the theories.

Monotony of Teaching Methods: Lack of Participatory Teaching Amid the Digital Divide. Existing MOOC resources mostly adopt a "PPT flipping + voice narration" model, lacking deep interaction. Learning analytics show that 71% of students remain passive in traditional classrooms, with insufficient engagement in higher-order thinking.

The breakthrough development of AIGC technology provides technical support to address these challenges. The AI large model, with its capabilities in natural language understanding, multimodal generation, and logical reasoning, has become a "cognitive translator" for theoretical teaching. By converting mathematical symbols into dynamic visual derivations, building cross-temporal case libraries, and providing personalized cognitive scaffolds, AIGC can reconstruct the teaching chain of "theoretical input—cognitive processing—meaning output," driving a paradigm shift from knowledge transmission to cognitive construction [1].

2 Theoretical Framework: Three Mechanisms of AIGC Empowering Pure Theoretical Teaching

Against the backdrop of deep integration between cognitive science and educational technology, AIGC technology reconstructs the knowledge transmission and construction pathways for pure theoretical courses through three mechanisms: concretization of symbolic systems, visualization of logical chains, and stratification of cognitive scaffolds.

2.1 Concretization of Symbolic Systems

By transforming abstract mathematical symbols into multimodal cognitive representations, this mechanism breaks the traditional disconnect between symbols and reality. For example, when explaining "image format conversion," AI can convert the mathematical formula for RGB-to-YUV color space conversion ($Y = 0.299R + 0.587G + 0.114B$) into a dynamic step-by-step animation. Students can adjust R, G, and B values via sliders to visually observe the independent variation patterns of brightness and color information. This concrete presentation is more intuitive than traditional blackboard teaching, improving students' correct understanding rate of color space conversion.

2.2 Visualization of Logical Chains

Through visual knowledge networks and counterfactual reasoning, this mechanism helps students build systematic cognitive structures. Taking the teaching of the "audio sampling theorem" as an example, AIGC can generate an interactive simulator: students manually adjust the sampling rate, and the system simultaneously displays comparisons between original and sampled waveforms while automatically annotating the mathematical derivation process of the Nyquist frequency. When students set the sampling rate below twice the highest frequency, the system triggers an alarm and demonstrates aliasing distortion. This dynamic reasoning deepens students' understanding of the application scenarios of the sampling theorem.

2.3 Stratification of Cognitive Scaffolds

Based on the zone of proximal development theory (Vygotsky, 1978), this mechanism provides differentiated support for students at different cognitive levels. In teaching "video frame rate," the intelligent Q&A system automatically adjusts difficulty based on students' questions: for foundational needs, it provides case comparisons of "visual differences between 24 fps and 30 fps"; for advanced needs, it generates mathematical models of "the physical relationship between frame rate and motion blur"; for innovative needs, it guides students to design "dynamic frame rate adaptive algorithms." Stratified scaffolds have been shown to improve students' higher-order thinking scores (analysis, evaluation, creation) in complex problem-solving tests.

These three mechanisms achieve synergistic effects through AI's capabilities in multimodal generation, logical reasoning, and dynamic decision-making: concretization of symbolic systems reduces extraneous cognitive load, visualization of logical chains provides thinking-path guidance, and stratification of cognitive scaffolds supports personalized development [2]. This integration shifts pure theoretical teaching from "symbolic indoctrination" to "cognitive construction," offering a systematic solution to teaching pain points such as difficulties in understanding basic concepts and cognitive transfer barriers [3].

3 Teaching Model Innovation Based on AI

In the Multimedia Technology course, the AI large model reconstructs the knowledge transmission mode of traditional pure theoretical classrooms through a three-stage teaching model: "theoretical visualization—logical concretization—cognitive systematization." This innovative model is student-centered, integrating multimodal generation, intelligent Q&A, and dynamic decision-making technologies to achieve a cognitive upgrade from "symbolic memorization" to "meaning construction" [4]. The teaching model of AI is illustrated in Figure 1.

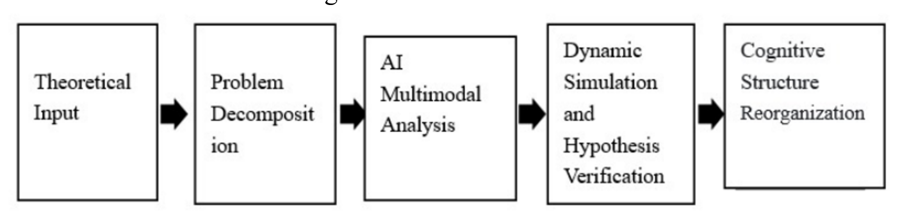

Fig. 1. AI teaching mode.

3.1 Visualization of Logical Chains

Problem-Driven Stage. Teachers set core questions based on curriculum standards (e.g.,"Why do JPEG images appear mosaic when enlarged?"), and AI automatically generates teaching packages containing typical cases, controversial perspectives, and interdisciplinary links. For example, when explaining image compression, the system provides synchronized image samples with different compression ratios, parameter comparisons of quantization tables, and mathematical explanations of compression artifact formation. This problem-oriented approach improves students' pre-class preview efficiency.

Concretization Presentation Stage. AI transforms abstract theories into interactive cognitive objects through multimodal generation technology. In teaching the "audio sampling theorem," the system generates an interactive simulator: students manually adjust the sampling rate (e.g., 44.1kHz, 22kHz), with the left side displaying real-time original sound waves and sampling points, and the right side synchronously annotating the mathematical derivation process of the Nyquist frequency formula $fs \geq 2fmax$. When students set the sampling rate below twice the highest frequency, the system triggers an alarm and demonstrates aliasing distortion. This dynamic deduction deepens students' understanding of the theorem's physical meaning.

Collaborative Construction Stage. Students work in groups to use AI for theoretical verification and innovative exploration. For example, in "video frame rate" teaching, groups can compare motion performance differences between 24fps and 60fps through the system's dynamic blur simulator and generate comprehensive analysis reports incorporating factors such as the principle of human visual persistence and hardware performance limitations. Teachers use an AI behavior monitoring system to capture students' thinking bottlenecks in real time (e.g., confusing frame rate with resolution concepts) and automatically push differentiated learning resources. Collaborative construction improves the completion rate of students' higher-order thinking tasks.

3.2 Innovation in Technology-Enabled Teaching Scenarios

AI automatically generates 3D knowledge graphs based on the curriculum outline, linking knowledge points such as "image format conversion" with color spaces and compression algorithms. Teachers can obtain lesson plan templates with teaching objectives, key/difficult points, and stratified assignments with one click, saving lesson planning time. The system also predicts students' cognitive misunderstandings—for example, in "RGB to CMYK" teaching, it pre-labels common errors such as "color gamut mapping loss."

Dual-Teacher Collaborative Classroom. Human teachers lead the teaching logic, while AI answers personalized questions in real time. For instance, when a student asks, "Why do mobile phone photos display differently on a computer?" the AI assistant generates a synchronized comparison chart of color gamut spaces, parses device profile files, and demonstrates the color management workflow. This "human-AI complementary" model improves classroom Q&A efficiency.

Dynamic Evaluation System. By analyzing students' interaction data with AI, the system automatically generates cognitive diagnosis reports [5]. For example, in the "audio coding" unit, if a student frequently adjusts bitrate parameters but cannot explain the relationship between bitrate and sound quality, the system pushes supplementary examples and suggests teachers strengthen the integration of theory and practice. This formative evaluation improves students' knowledge retention rate.

4 Conclusion

This study uses AIGC technology as a pivot to leverage the deep logic of pure theoretical course teaching reform. By constructing a three-stage teaching model of "theoretical visualization—logical concretization—cognitive systematization," it achieves a paradigm shift from symbolic memorization to cognitive construction. Empirical data show significant improvements in three dimensions: accuracy of conceptual understanding, logical reasoning ability, and learning engagement, verifying the educational value of AIGC as a "cognitive translator."

The research breaks through the temporal and spatial limitations of traditional teaching, creatively transforming AI's multimodal generation capabilities into dynamic deduction tools to establish intuitive mappings between mathematical symbols and physical phenomena. Through the organic integration of intelligent lesson planning systems, dual-teacher collaborative classrooms, and dynamic evaluation systems, a complete teaching chain of "problem-driven—concretized presentation—collaborative construction" is formed. This virtual-reality integrated teaching paradigm retains the logical framework led by teachers while unleashing the potential of AI's personalized support, providing a systematic solution to teaching pain points such as knowledge lag and cognitive disconnection.

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