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Cracking the Abstract Barrier: Application and Practice of AI-Powered Dynamic Visualization in Organic Chemistry Teaching

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Abstract: *Organic reaction mechanisms involve electron transfer, orbital hybridization, and changes in molecular spatial configuration—microscopic processes that constitute a major teaching challenge in the vocational undergraduate Organic Chemistry course. Traditional instruction relies on blackboard work and static structural formulas, which leads students to memorize reaction equations mechanically and leaves them with insufficient spatial imagination and mechanistic reasoning. This study introduced AI-powered dynamic visualization into the classroom and developed a blended teaching model combining "theoretical lecture + AI-based dynamic mechanism demonstration + in-class virtual inquiry," covering the full process of pre-class preview, in-class instruction, and post-class consolidation. Two parallel classes in Pharmaceutical Engineering were selected for a controlled teaching study, and teaching effectiveness was evaluated using course scores, questionnaires, and semi-structured interviews. The results show that AI visualization can concretize microscopic processes, reduce cognitive load, and significantly improve students' higher-order abilities in mechanism derivation and stereochemical analysis. At the same time, problems were identified, including professional errors in AI-generated materials, student dependence on tools, and insufficient digital teaching competence among teachers. Accordingly, optimization strategies are proposed: building a standardized repository of mechanism visualization resources, balancing AI demonstrations with independent reasoning practice, and strengthening teacher training in AI-supported teaching. These findings provide practical reference for intelligent teaching reform in similar courses.*

Keywords: *artificial intelligence; dynamic visualization; organic reaction mechanisms; blended teaching; vocational undergraduate education*

1. Introduction

Organic Chemistry is a required foundational course for majors such as pharmacy, biology, and materials science. Organic reaction mechanisms form the core of the course and directly affect subsequent learning in drug synthesis, fine chemicals, and related fields. Organic reactions are microscopic dynamic processes; bond cleavage and formation, electron flow, and chiral configuration inversion cannot be observed directly. Traditional teaching relies on blackboard writing and static PowerPoint slides, which can display only reactants and products. The microscopic dynamic process depends on the instructor's verbal description and places high demands on students' spatial imagination. As a result, students commonly memorize reactions by rote, have weak knowledge transfer ability, and create a dilemma in which "teachers find it difficult to teach and students find it difficult to learn"[1].

The rapid development of generative AI has made AI molecular visualization tools capable of rapidly constructing 3D molecular models and generating reaction animations, offering a new pathway for addressing the abstract teaching challenges of mechanisms[2]. At present, domestic applications of AI in chemistry education are mostly concentrated on intelligent question banks and AI question answering; full-process classroom empirical research on organic reaction mechanisms is relatively scarce, and technology often becomes disconnected from teaching content, with a lack of complete controlled teaching data[3]. This issue is especially salient in vocational undergraduate institutions, where students' chemistry foundations vary considerably and digital tools are needed to support differentiated instruction.

Against this background, this study focuses on the vocational undergraduate teaching context, integrates AI-powered dynamic visualization into the entire chain of organic chemistry teaching,

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adheres to teacher leadership with AI as a cognitive scaffold, conducts a one-semester controlled teaching practice, examines teaching outcomes, and identifies practical problems and improvement plans.(For details, please refer to Figure 1.)

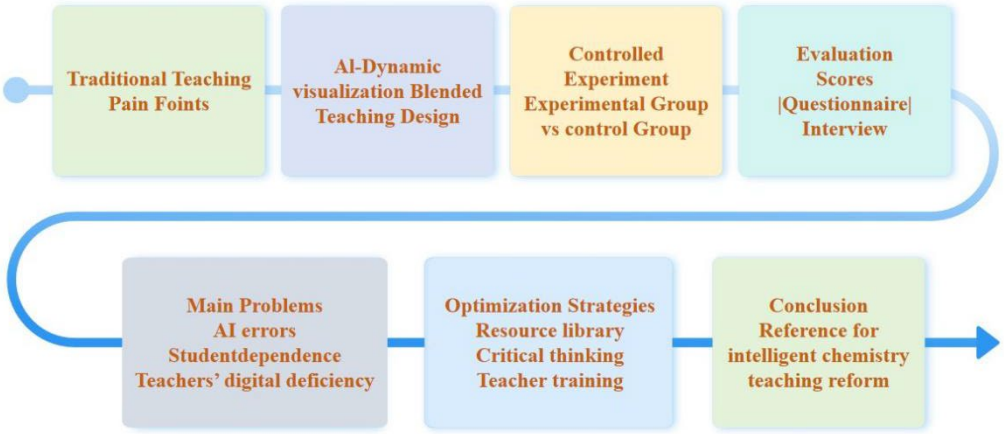


Figure 1: Overall Design and Implementation Path of This Study

2. Main Difficulties in Learning Organic Reaction Mechanisms under Traditional Teaching

First, microscopic mechanisms are abstract, and students' spatial imagination is notably weak. For topics such as SN2 backside attack, chiral Walden inversion, and carbocation rearrangement, static images can capture only instantaneous structures and cannot present continuous evolution, making it easy for students with weaker foundations to confuse stereochemical rules. Traditional two-dimensional teaching media struggle to present dynamic changes in three-dimensional molecular conformations, resulting in cognitive obstacles in stereochemistry[2].

Second, teaching methods are monotonous, and the efficiency of overcoming key difficulties is low. When explaining complex mechanisms, teachers spend substantial class time on oral derivation. Owing to reagent toxicity and class-hour constraints, many synthesis experiments corresponding to these mechanisms cannot be performed, leaving theory disconnected from practice.

Third, students engage in surface learning and lack logical reasoning training. Students are accustomed to reciting equations but do not understand the underlying logic of reactions, and they cannot independently derive products when conditions change. Memorizing reaction results while neglecting mechanistic logic is a common phenomenon of surface learning in organic chemistry[1].

Fourth, in large-class teaching, feedback on learning conditions is delayed, making differentiated instruction difficult to implement. Instruction relies on summative end-of-term written examinations and lacks process data, making it difficult to identify students' cognitive misconceptions in a timely manner; polarization in learning becomes obvious. Traditional assessment models struggle to capture students' microscopic thinking processes and are not conducive to precise teaching interventions[3].

3. Design of the AI-Based Mechanism Visualization Blended Teaching Model

3.1 Overall Approach

A trinity teaching model was constructed comprising pre-class preview, in-class lecture and dynamic demonstration, and post-class consolidation and review. AI serves only as an auxiliary cognitive tool and does not replace basic theoretical instruction. AI-generated 3D interactive models and reaction mechanism animations are used to visualize electron transfer, transition states, and configuration inversion, promoting a shift from mechanical memorization to understanding-based learning. Visualization technology can transform unobservable microscopic chemical processes into intuitive visual signals and effectively reduce learners' cognitive load[6].

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3.2 Core Application Scenarios

Based on the course knowledge modules, four core application scenarios were identified. The first is stereochemistry demonstration: for enantiomerism and conformational transformation, molecules can be rotated and disassembled from multiple angles, and three-dimensional interaction helps students establish spatial concepts of molecules[6-7]. The second is dynamic demonstration of typical reaction mechanisms: SN1/SN2, E1/E2, electrophilic addition, and rearrangement reactions, with complete presentation of intermediates, transition states, and electron flow; however, it should be noted that generative AI outputs of mechanistic content carry potential error risks and cannot be used directly without review[4-5]. The third is virtual inquiry scenarios: for hazardous or time-consuming synthesis reactions, AI virtual simulation allows students to change reaction conditions and compare differences in reaction pathways, extending the boundaries of physical experimental teaching[7]. The fourth is personalized learning support: combined with an intelligent exercise bank, visualized resources are pushed to students according to their incorrect answers, facilitating differentiated instruction[8-9].

3.3 Full-Process Teaching Implementation

Before class: the teacher screens and verifies AI-generated 3D models and mechanism animations, uploads them to the teaching platform, assigns preview tasks and short quizzes, and adjusts classroom emphases according to preview data. During class: basic theoretical concepts are first taught; then, for difficulties revealed in the preview, AI dynamic materials are played using a "demonstration–pause–questioning–student handwritten derivation" procedure, and group discussions are organized to analyze and distinguish reaction mechanisms, avoiding students' passively watching animations. If students merely watch visualization animations passively and lack independent derivation, cognitive inertia may occur and the effect of logical training may be weakened[10]. After class: all visualization resources are made available, tiered exercises are assigned, incorrect answers are automatically linked to mechanism animations; students are encouraged to try constructing simple molecular models, and student feedback is collected to iteratively improve teaching resources.

4. Teaching Practice and Effect Analysis

4.1 Participants and Scheme

Two parallel classes in the vocational undergraduate Pharmaceutical Engineering program at the university were selected as research participants. The experimental class (42 students) adopted the AI visualization blended teaching model, while the control class (41 students) continued with conventional teaching using blackboard writing and static PowerPoint images. Both classes were taught by the same teacher, and the syllabus, teaching hours, textbook, and after-class assignments remained consistent. A pre-enrollment chemistry foundation test showed no statistically significant difference between the two classes, indicating suitable conditions for a controlled experiment. The practice lasted one full semester. The experimental class strictly followed the pre-class, in-class, and post-class full-process design. Before the project, the research team completed the selection of AI tools, established standards for material generation and proofreading, and specified that AI-produced mechanisms, configurations, and related content must be professionally verified by the instructor before use. A multi-dimensional evaluation scheme was adopted, combining midterm and final course tests, an anonymous end-of-term questionnaire, and semi-structured student interviews.

4.2 Comparison of Course Scores

Statistical results showed that the overall average score of the experimental class was higher than that of the control class. Further analysis by item type showed that the gap between the two classes was small on memory-based basic questions; however, on higher-order thinking items such as mechanism derivation and stereochemical analysis, the experimental class showed more pronounced improvement. This indicates that AI visualization teaching has limited effect on simple knowledge memorization but can effectively help students build an overall understanding of microscopic reaction processes, promote a shift from"remembering reaction results" to "understanding reaction logic," and enhance higher-order abilities such as mechanism derivation and stereochemical analysis.

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4.3 Feedback on Learning Experience

A total of 83 valid samples were collected from the end-of-term questionnaire. Most students in the experimental class believed that dynamic visualization reduced the difficulty of understanding mechanisms. About 76.2% reported that dynamic demonstrations helped them understand electron transfer and configuration inversion, their fear of difficulty was alleviated, and their course interest increased markedly. At the same time, some students noted that they could not merely watch animations and still needed to write mechanisms themselves. In the control class, more than half of the students reported difficulties in imagining stereochemistry and reaction mechanisms and greater learning pressure.

In the experimental class, four students were selected from each of the high-, medium-, and low-achievement levels for semi-structured interviews. Students generally acknowledged that AI dynamic visualization "makes invisible reactions intuitive," with particularly clear benefits for difficult points such as SN2 configuration inversion and carbocation rearrangement. Students with weaker foundations could repeatedly review animations to compensate for insufficient classroom understanding, while more advanced students hoped for more visualization resources on complex reactions. The interviews also revealed potential risks: a small number of students were satisfied with watching animations, were unwilling to perform handwritten derivation, and exhibited a phenomenon of "understanding when watching but unable to write it out."

5. Reflection on Problems and Optimization Strategies

One semester of practice showed that AI visualization significantly empowered organic chemistry teaching, but three problems remained. First, AI-generated materials contain professional errors. Automatically produced mechanism animations and transition-state structures occasionally show incorrect chemical bonds, electron flow, or stereochemical configurations; direct use without professional verification by the teacher can mislead students' cognition. Second, some students became dependent on visualization materials, habitually watching demonstrations passively and omitting training in mechanism derivation and drawing electron-transfer arrows. Third, frontline chemistry teachers generally lack systematic training in AI material production and editing, and producing high-quality materials is time-consuming, limiting the large-scale dissemination of this model.

In response to the above problems, three optimization strategies are proposed. First, establish a shared repository of organic mechanism visualization resources. The course teaching team should divide labor to develop and review 3D models and dynamic animations of typical reaction mechanisms, formulate standards for AI material generation and proofreading, and ensure that each resource is reviewed by a subject teacher before being included, thereby enabling resource reuse and reducing the burden on individual teachers. Second, balance AI demonstrations with students' independent reasoning training. The classroom procedure of "demonstration–pause–questioning–handwritten derivation" should be maintained; after watching animations, students must write mechanisms by hand and analyze reaction pathways. Students should be clearly informed that visualization materials are only auxiliary cognitive scaffolds and cannot replace mechanism-writing training. Third, strengthen the construction of teachers' digital competence. Special workshops should be conducted on the use of AI molecular visualization tools, material proofreading, and instructional design. At the same time, considering the characteristics of vocational undergraduate education, visualization teaching should be extended to virtual simulation experiments, and elements such as green chemistry and values-oriented education should be incorporated into cases, achieving unity between knowledge transmission and value guidance.

6. Conclusion

To address the teaching pain point that organic reaction mechanisms are microscopic and abstract, this study constructed a blended teaching model of "theoretical lecture + AI-based dynamic mechanism demonstration + in-class virtual inquiry," covering the full process of pre-class preview, in-class discussion, and post-class review. A one-semester controlled teaching practice showed that this model can effectively reduce students' cognitive load, improve their understanding of reaction mechanisms and stereochemistry, enhance higher-order logical derivation ability, and stimulate learning interest. The study also revealed practical challenges, including professional bias in AI materials, student dependence on tools, and insufficient digital competence among teachers, and addressed them by

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building a standardized and verified visualization resource repository, strengthening reasoning training, and cultivating teaching staff. Future work will further expand the sample and improve the multi-dimensional evaluation system, providing reference for intelligent teaching reform in similar basic science courses in vocational undergraduate and regular higher education institutions.

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