Scientific Research Publishing

Open Journal of Social Sciences, 2026, 14(6), 392-401
https://www.scirp.org/journal/jss
ISSN Online: 2327-5960
ISSN Print: 2327-5952

AI-Enhanced Problem-Based Learning in Pathology Technology: An OBE-Driven Triadic Model of Clinical Problem, AI Validation, and Research Innovation

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How to cite this paper: Li, Y. L., Zhu, X. Y., Lu, F. Y., Zhao, Z. W., Liu, C. Y., & Cao, D. M. (2026). AI-Enhanced Problem-Based Learning in Pathology Technology: An OBE-Driven Triadic Model of Clinical Problem, AI Validation, and Research Innovation. *Open Journal of Social Sciences, 14,* 392-401.
https://doi.org/10.4236/jss.2026.146023

Received: May 17, 2026
Accepted: June 21, 2026
Published: June 24, 2026

Abstract

Objective: This study aimed to evaluate the efficacy of an innovative triadic instructional model—integrating Outcome-Based Education (OBE) with a "Clinical Problem-AI Validation-Research Innovation" framework—in graduate-level Pathology Technology education. **Methods:** A cohort of 72 academic postgraduate students in clinical medicine (enrolled in 2024 and 2025) was instructed using this model. Guided by OBE principles, the curriculum was restructured around a progressive learning pathway: "from specimen to data, from protein to nucleic acid, from two-dimensional to three-dimensional, and from single-omics to multi-omics". Key strategies included defining clear learning outcomes, backward course design, deep integration of AI tools, problem-based learning (PBL) case drivers, and a multidimensional assessment system. **Results:** The intervention yielded high student satisfaction, with 96% reporting enhanced learning motivation and 92% affirming that AI tools improved their experimental design efficiency. The rate of "excellent" performance on final examinations increased from 68% to 82% (a 14-percentage-point gain). Furthermore, the success rate for university-level research project grants rose from 28% to 43% (a 15-percentage-point increase), and the proportion of high-quality research proposals climbed from 35% to 46% (an 11-percentage-point improvement). **Conclusion:** The "OBE + Triadic Model" effectively enhances graduate students' clinical reasoning, research innovation capabilities, and technical proficiency by leveraging authentic clinical problems as drivers, AI as an enabler, and research innovation as an extension.

*These authors contributed equally to this work.

Keywords

Artificial Intelligence, Problem-Based Learning, Pathology Technology, Outcome-Based Education, Instructional Design

1. Introduction

The ongoing advancement of the "New Medical Sciences" initiative is catalyzing a profound transformation in medical education, shifting its focus from knowledge transmission to competency development. China's Guiding Opinions on Accelerating the Innovative Development of Medical Education explicitly calls for reforms in classroom instruction to strengthen the cultivation of students' clinical reasoning and research innovation capacities[1]. Similarly, the "Healthy China 2030" Planning Outline emphasizes the need to foster interdisciplinary, innovative medical professionals[2]. Within this context, Pathology Technology, a pivotal bridging course between basic science and clinical practice, has become a critical focal point for enhancing the comprehensive competencies of medical postgraduates.

Traditional Pathology Technology instruction has long been constrained by a triad of persistent challenges: static case resources, delayed pedagogical feedback, and a deficit in research-oriented thinking. These issues not only hinder students' ability to grasp the complexity of clinical scenarios and correct cognitive biases in a timely manner but also create a disjunction between technical training and the development of innovative capacity. The rapid evolution of artificial intelligence (AI) offers a transformative opportunity for medical education. Breakthroughs in AI-driven image recognition and data mining have elevated AI from a mere auxiliary tool to a "cognitive amplifier" capable of reshaping the entire pedagogical workflow. Existing research indicates that AI-augmented PBL can enable personalized resource delivery and immediate feedback (Chen & Dan, 2025; Fan, Deng, Ding, & Liu, 2025), and that multimodal AI-integrated models can effectively enhance clinical decision-making skills (Jiang et al., 2026; Zhang et al., 2025). However, most current studies focus on the empirical validation of technological applications, with limited systematic construction of pedagogical models from a cognitive theory perspective and a lack of theoretical explanation for the core question of "how AI facilitates deep learning" (Fan & Song, 2025; Zhuang et al., 2024).

To address this gap, our study constructs a "Clinical Problem-AI Validation-Research Innovation" triadic instructional model, grounded in a synthesized theoretical framework of constructivist learning theory, situated learning theory, and cognitive load theory, and designed according to OBE principles. The model's theoretical logic is threefold: 1) authentic clinical cases establish a "problem space" (situated learning); 2) AI tools facilitate "cognitive offloading" to reduce extraneous cognitive load; and 3) research innovation tasks drive "competency transfer"

[1]https://www.gov.cn/zhengce/zhengceku/2020-09/23/content_5546373.htm?ivksa=1023197a

[2]https://www.mofcom.gov.cn/zcfb/zgdwjjmywg/art/2017/art_5808daa8f56e4dabaa08dcd254db897f.html

to promote deep learning. This framework not only responds to the practical dilemmas of traditional teaching but also provides an interpretable mechanistic model for AI-empowered medical education.

2. Methods

2.1. Study Design

This study was a single-center educational intervention with a historical comparison design, conducted at Youjiang Medical University for Nationalities between 2023-09 and 2026-02. The pre-reform cohort (n = 34) comprised clinical medicine postgraduate students from the 2023 enrollment year who completed the traditional pathology technology curriculum from 2023-09 to 2024-02. The post-reform cohort (n = 72) included clinical medicine postgraduate students from the 2024-2025 enrollment years who participated in the newly implemented "Clinical Problem-AI Validation-Research Innovation" teaching model from 2024-09 to 2026-02. Inclusion criteria for both cohorts: 1) full-time clinical medicine postgraduate students; 2) completed the entire curriculum during the study period; 3) provided informed consent for data collection.

The same instructor team, "the Pathology Technology Teaching Team from the Medical Laboratory Technology Teaching and Research Office at Youjiang Medical University for Nationalities", delivered all teaching activities for both pre- and post-reform cohorts, with no major changes in core faculty members across the three enrollment years (2023-2026). Assessment standards, examination protocols, grading rubrics, and project evaluation criteria remained consistent throughout the study period to ensure methodological validity and fair comparison of educational outcomes.

2.2. Course Objectives and Theoretical Framework

The Pathology Technology course bears a triple mission: to connect foundational science, serve clinical practice, and support research (Lu et al., 2024). Its content spans from morphological to molecular domains and integrates theory with technique, resulting in high knowledge density and demanding operational requirements. Students often struggle with a "triple difficulty": memorizing principles, performing procedures, and linking knowledge to clinical contexts (Wang et al., 2023; Yang, Zheng, Wen, & Zheng, 2023).

Our triadic model is designed to overcome the "static cases, delayed feedback, and absent research mindset" challenges. It is not a simple concatenation of three steps but a progressive logic: engaging students with authentic problems, assisting them with intelligent tools, and elevating them through research tasks.

OBE Principle: The core of OBE is "starting from the end". We first defined four key learning outcomes: knowledge application, technical proficiency, clinical reasoning, and research innovation. All subsequent module design, AI integration, and assessment were aligned with these outcomes.

Clinical Problem-Driven: Each session begins with a real clinical case (e.g., "A

32-year-old non-smoking female with an ALK-positive lung biopsy—does she truly require targeted therapy?"). This creates "cognitive conflict", stimulating curiosity and providing a contextual anchor for abstract techniques (e.g., FISH, PCR).

AI Validation Empowerment: AI tools are embedded to handle low-level, repetitive tasks, freeing cognitive resources for higher-order thinking. For instance, QuPath automates image segmentation, large language models (e.g., DeepSeek, Kimi) expedite literature review, and Labster provides virtual simulation for procedural practice. AI also offers immediate feedback, overcoming the "act-then-evaluate" delay of traditional methods.

Research Innovation Extension: Each module culminates in a research task where students formulate a testable hypothesis and draft a preliminary study design (e.g., "Do different EML4-ALK fusion variants affect crizotinib efficacy?"). This bridges the gap between technical execution and scientific inquiry, fostering a transition from "technician" to "researcher".

This "Problem → Tool → Innovation" closed-loop is more effective at stimulating student agency and creativity than the traditional linear "lecture-then-practice" approach.

2.3. Implementation and Module Reconstruction

The course was restructured into a closed-loop system: Clinical Problem as Driver: Authentic cases are used to extract scientific questions from diagnostic uncertainty, therapeutic decisions, and prognostic evaluation, thereby motivating learning and building a link between technology and clinical decision-making.

AI Validation as Enabler: A suite of AI tools was systematically integrated: Large Language Models (DeepSeek, Kimi) for conversational Q&A and knowledge retrieval. QuPath for automated segmentation and quantitative analysis of pathology images. Primer-BLAST for primer design and sequence optimization. OncoKB for interpreting the clinical significance of gene mutations and Labster for simulated laboratory training.

Research Innovation as Extension: Students are encouraged to design novel research protocols, analyze data with AI, and draw scientific conclusions, achieving a leap from "learning techniques" to "conducting research".

2.4. Teaching Process Design

A three-stage (pre-class, in-class, post-class) progressive workflow was designed, with AI deeply embedded in each phase (**Figure 1**). The "ALK rearrangement validation" module serves as an example.

Pre-class: A de-identified clinical case was released on the learning platform with guiding questions. Students watched micro-videos on relevant techniques (e.g., FISH, PCR) and used AI tools to research "ALK fusion testing consensus". Their pre-test results generated a class "learning profile" for the instructor to tailor the lesson.

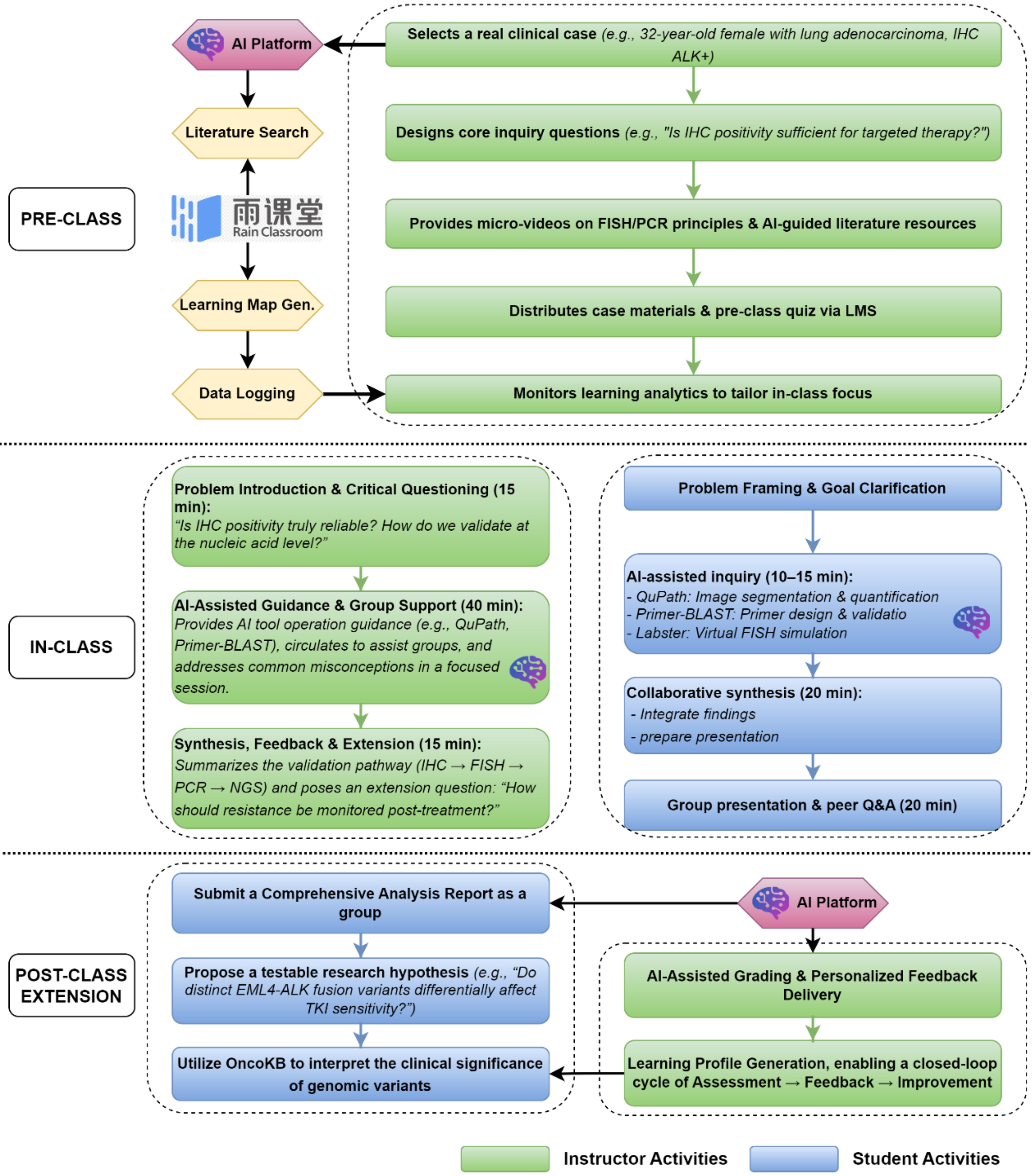

Figure 1. Implementation workflow of the "Clinical problem-AI validation-Research innovation" triadic instructional model.

In-class: The session followed a structured flow:

Problem Introduction: The instructor presented the case's core dilemma (e.g., "Does IHC positivity alone justify targeted therapy?").

AI-Assisted Inquiry: Students worked in groups using QuPath to analyze tissue slides, Primer-BLAST to design primers, and Labster to simulate FISH procedures.

Collaborative Construction: Groups synthesized their findings to form a conclusion or hypothesis (e.g., "FISH confirms rearrangement; a TP53 co-mutation subclone may drive resistance").

Presentation & Feedback: Selected groups presented their work, followed by peer questioning and instructor critique, which summarized the "IHC → FISH → PCR → NGS" validation pathway and posed an extension question.

Post-class: Groups submitted a "Comprehensive Analysis Report" outlining a technical roadmap, result interpretation, and clinical recommendations. An AI-assisted grading system provided initial feedback, which was then refined by the instructor. High-quality reports were encouraged to be developed into formal research proposals.

2.5. Outcome Measures

The following outcome metrics were defined and calculated as follows:

Mastery rate: Proportion of students achieving ≥ 80% on the comprehensive theoretical examination. Denominator = total number of students in each cohort. Calculated per student.

Excellent performance: Proportion of students scoring ≥ 90% on the comprehensive theoretical examination. Denominator = total number of students in each cohort. Calculated per student.

High-quality proposal: Proportion of research proposals receiving "excellent" rating (≥85 points) from the expert review panel based on predefined criteria (innovation, feasibility, scientific rigor). Denominator = total number of proposals submitted. Calculated per proposal.

Grant success rate: Proportion of student research proposals that successfully secured external funding (university-level or higher research grants). Denominator = total number of proposals submitted for funding. Calculated per proposal.

2.6. Survey Instrument

Student learning satisfaction was assessed using a post-course survey administered via Wenjuanxing (Questionnaire Star), a WeChat mini-program platform. The survey took approximately 10 minutes to complete and evaluated multiple dimensions including teaching content, teaching methods, instructional organization, and instructor attitude. A 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree) was employed for all items. The survey was conducted anonymously to ensure honest feedback, and all responses were collected electronically for analysis.

2.7. Statistical Analysis

This study employed a descriptive analytical approach for comparing pre- and post-reform outcomes. No inferential statistical testing was performed. All reported metrics (mastery rate, excellent performance, high-quality proposal rate, and grant success rate) are presented as descriptive proportions to illustrate the observed differences between the historical control cohort and the intervention cohort. The findings should be interpreted as preliminary observations that demonstrate the potential impact of the educational intervention, warranting further investigation with larger sample sizes and rigorous statistical testing in future studies.

3. Results

An OBE-aligned, multidimensional assessment system was constructed to evaluate knowledge, ability, and professionalism (Table 1). The implementation of the triadic model yielded significant positive outcomes across all three assessed dimensions.

Table 1. OBE-aligned assessment framework for the triadic model.

Goal Dimension	Assessment Content	Tools	Data Collection
Knowledge Internalization	Mastery of principles, logical connections between techniques, accuracy on PBL case questions	Modular quizzes, knowledge graph comparison, concept mapping	LMS auto-grading & Instructor review
Competency Attainment	AI tool proficiency, logical design of experiments, data interpretation	AI usage logs, peer/self-assessment, lab reports, comprehensive proposals	System logs & Peer review & Instructor scoring
Professionalism Development	Scientific attitude, patient-centeredness, ethical decision-making, innovation	Ethical scenario tasks, proposal innovation score, peer evaluation	Classroom observation & Instructor/peer evaluation

First, with respect to knowledge internalization, the data indicate a substantial deepening of conceptual understanding. Post-module assessments revealed that students achieved a 92% mastery rate in core "principles and applications" of pathology technologies. Notably, their grasp of the more complex and clinically critical concept—the "appropriate use and limitations of different techniques"—exceeded 85%. This represents a remarkable 28-percentage-point improvement from their pre-class baseline. This finding suggests that the model's problem-driven approach, which anchors abstract technical knowledge within authentic clinical contexts, is highly effective in moving students beyond rote memorization towards a functional and integrated understanding of the subject matter.

Second, the assessment of competency attainment demonstrated high levels of student engagement and practical skill development. The survey, which achieved a 100% response rate (N = 72), showed that at least 92% of students either "agreed" or "strongly agreed" with the model's effectiveness. Objective metrics from the learning management system further corroborated this self-reported satisfaction: task completion rates for key AI tools were consistently high (QuPath: 96%, Primer-BLAST: 94%, literature search: 98%). Crucially, all student groups successfully completed the capstone "comprehensive proposal" task, and 46% of these proposals were evaluated as high-quality, demonstrating logical experimental design and innovative thinking. This convergence of subjective and objective data strongly supports the conclusion that the integration of AI as a cognitive partner empowers students to efficiently execute complex technical tasks and develop preliminary research competencies.

Third, the cultivation of professionalism was evident in students' qualitative performance during case discussions and ethical scenarios. Students consistently exhibited sophisticated clinical judgment by integrating multiple factors into their decision-making, such as patient benefit, diagnostic accuracy, and cost-effectiveness. A representative example was the reasoned argument made by several groups advocating for a stepwise diagnostic approach (e.g., FISH before NGS for initial ALK testing) to balance precision medicine with resource stewardship. Furthermore, in structured ethical decision-making tasks, over 90% of students adopted a clearly patient-centered perspective, focusing on the implications of test results for the patient's well-being and treatment options. These observations suggest that the model successfully fosters not only technical and cognitive skills but also the essential humanistic values of a future physician-scientist.

Table 2. Key performance indicators before and after reform.

Dimension	Metric	Pre-Reform	Post-Reform
Satisfaction	Course stimulated interest	—	96%
	AI improved design efficiency	—	92%
Research Capacity	University grant success rate	28%	43%
	High-quality proposal rate	35%	46%
Technical Skill	Final exam excellence rate	68%	82%

(Note: Pre-reform data from 34 students in the 2023 cohort; Post-reform from 72 students in 2024-2025 cohorts.)

The overall impact of the pedagogical reform is summarized in **Table 2**, which shows significant improvements across all key institutional metrics, including a 14-percentage-point rise in final exam excellence rates and a 15-percentage-point increase in university-level research grant success.

4. Discussion

This study demonstrates that the "Clinical Problem-AI Validation-Research Innovation" triadic model, underpinned by OBE, is a powerful framework for modernizing Pathology Technology education. Its success stems from a synergistic mechanism: authentic clinical problems ignite intrinsic motivation; AI tools act as cognitive prosthetics, enabling efficient information processing and immediate feedback; and research innovation tasks scaffold the transfer of knowledge into genuine scientific inquiry (Li et al., 2026; Xie & Lu, 2025).

The data reveal a clear shift from passive knowledge reception to active, self-directed learning. The high engagement in AI tool usage and the quality of research proposals confirm that students are not just learning about technology but are learning to use it as a partner in scientific discovery (Huang, 2025). The observed gains in professionalism further suggest that the model fosters a holistic development of the future physician-scientist.

However, our reflection identified a key bottleneck: the transition from AI-assisted signal interpretation (e.g., FISH) to independent scientific reasoning about complex concepts like clonal evolution remains challenging for some students. This highlights a crucial "last-mile" problem in the triadic chain.

5. Conclusion and Future Directions

Our OBE-guided triadic model has proven effective in enhancing graduate students' clinical, research, and technical competencies in Pathology Technology. Its core innovation lies in its theoretically grounded, closed-loop design that leverages AI not just as a tool but as a catalyst for deep learning.

Future work will focus on three areas to address the identified bottleneck and scale the model: 1) integrating dynamic simulation platforms (e.g., Cancer Simulator) to visualize clonal dynamics under therapeutic pressure; 2) developing a tiered library of real-world FISH cases within QuPath for targeted skill refinement; and 3) advancing our learning analytics platform to generate individualized "learning portraits" for precision teaching. By continuously refining this model, we aim to provide a replicable blueprint for "New Medical Sciences" talent development across a broader range of medical technology courses.

Acknowledgements

This work was supported by the 2025 Guangxi Graduate Education Innovation Program (JGY2025335).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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