

Research on the Construction of AI-Empowered College Physics Experiment Courses

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Abstract: Driven jointly by the national strategic initiative on educational digitalization and the "Artificial Intelligence+" action plan, physics experiment teaching is undergoing a critical transition from traditional hands-on operations to intelligent inquiry-based learning. However, current research on AI-empowered experimental teaching largely relies on expensive specialized equipment or cloud-based computing resources, which entails high deployment costs, significant data privacy risks, and limited feasibility for widespread adoption in ordinary colleges and universities. Grounded in the principles of lightweight design, low cost, and high availability, this study systematically develops a theoretical framework and practical pathways for constructing AI-enhanced university physics experiment courses. The proposed approach centers on open-source large language models and retrieval-augmented generation (RAG) techniques to build a domain-specific knowledge system for physics experiments, and achieves data security and cost control through local deployment. We establish a tripartite construction pathway encompassing knowledge base development, vertical AI model customization for the course, and intelligent teaching applications. Furthermore, we design a human-computer collaborative instruction model that integrates AI-assisted preview, instructor-led focused instruction, and a two-stage assessment comprising AI initial evaluation followed by instructor verification, thereby forming a closed-loop intelligent teaching system covering the entire spectrum of instruction, learning, administration, evaluation, and assessment. The findings indicate that this model effectively mitigates the hallucination issue inherent in general-purpose large models when applied to specialized domains, improves the quality of students' experimental reports, and enhances their autonomous inquiry capabilities. It also offers a replicable, cost-effective reform blueprint for resource-constrained local institutions.

Keywords: artificial intelligence; university physics experiment; smart course; knowledge graph; retrieval-augmented generation; lightweight deployment

1. Introduction

1.1 Research Background

In 2025, the Ministry of Education launched a strategic action on digital education; According to The State Council's "AI+"; Guidelines require integrating AI into each aspect of teaching leads to educational transformation towards capacity improvement. Physics experiments which is one key part of science and engineering education has always been plagued with the dilemma of focusing on reporting but neglecting methodology reflection, local colleges and universities can't afford the high cost of hardware and API for intelligent upgrade.

1.2 Domestic and International Research Status

Institutions such as University of Oxford, Peking University, Shanghai Jiao Tong University have conducted some AI assisted physics experiments to verify the possibility of improving teaching quality; Most use expensive special equipment or cloud computing power with high cost, great privacy risk, difficult for popularization. Chen Hongzhang pointed out the restructuring of AI application system, lack of data platform; Case study by Shen Huiming et al., based on "Double First-Class" resources; Meng Yakun emphasized that the quality of knowledge base is decisive to RAG "hallucinations"; Liu Chang et al. face professional and dependent problems, Liang Zhumei et al advocated teacher-led agent reconstruction, He Chunying et al. verified the effectiveness of the "teaching - learning - management - evaluation - testing" closed loop.

1.3 Research Questions and Objectives

Our objective is to develop an accurate and stable AI system in physics experiments and a scalable teaching model with no additional hardware or costly APIs: We want to construct a "lightweight, low-cost, and highly available" theoretical framework and a full-process smart teaching model.

2. Theoretical Foundations and Core Concepts

2.1 Smart Courses

Three transformations in smart courses focusing on students with generative AI and big data to achieve blended personalized learning and iterative optimization include: shift of organization from linear to three-dimensional networks; shift of interaction from one-way to a data-driven closed loop; and shift of support from scale-based to personalized.

2.2 RAG Technology

Retrieval-Augmented Generation retrieves relevant documents from a knowledge base and feeds them along with the question into a large model that is restricted to answering based on facts. Advantages: Less hallucination; Dynamic update; Traceable sources; Lightweight model + high quality knowledge base reaches as close to a large model.

2.3 Human-AI Collaborative Teaching

Collaboration among teachers, AI, and students: AI -- standardized transmission and first assessment; Teachers -- higher order thinking and complex diagnosis; Students are active constructors of knowledge. Chen Hongzhang proposed "teacher-AI-student triadic collaboration." Liang Zhumei et al., advocated moving from passive questioning to autonomous exploration.

3. Construction Framework for AI-Empowered Physics Experiment Courses

3.1 Overall Architecture Design

The framework that we developed for AI-empowered physics experiment courses built in our study consists of three layers as shown in Figure 1: foundation-building a dedicated knowledge base (textbooks, grading rubrics, error cases, sample reports, etc.), model integration-lightweight open-source models (Qwen2/Phi-3) based on RAG deployed with quantization, and application development-an intelligent learning companion, operation prompts, initial report evaluation, and learning analytics.

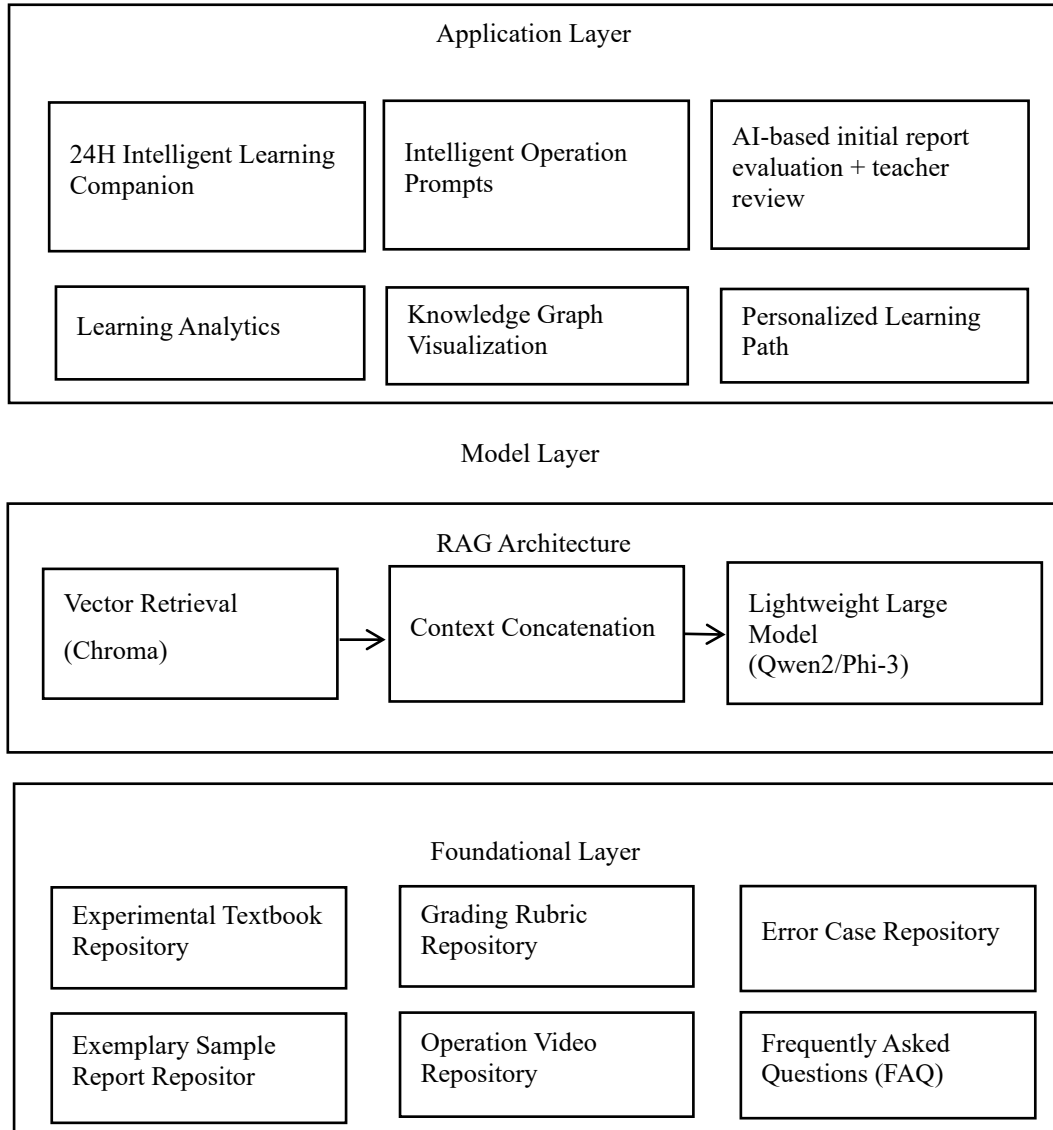


Figure 1 Overall Architecture of AI-Empowered Physics Experiment Courses

3.2 Knowledge Base Construction: Knowledge Organization in a Vertical Domain

The quality of knowledge base construction determines, to a certain extent, the quality of vertical models for AI courses.

3.2.1 Knowledge Graph Layer

This layer is a structured knowledge network. This layer breaks down the content in physics experiment courses into related knowledge elements. For example, for the spectrometer experiment, we have nodes: instrument structure (telescope, collimator, stage), adjustment principles (autocollimation method, half-and-half adjustment method), measurement methods (determination of grating constant, wavelength measurement) and error analysis (sources of systematic and random errors). The causal, progressive and parallel relationship between them has been annotated on this graph.

3.2.2 Question Graph Layer

It is a hierarchy of an inquiry index based on the knowledge graph that designs a three-level question framework including global level questions ("Why must a spectrometer be adjusted to three perpendicular conditions?"), conceptual-level questions("What is the optical path principle of the autocollimation method?"), methodological-level questions("How can one determine whether the telescope optical axis is perpendicular to the central axis of the spectrometer?"), to guide students going from rote memorization to problem solving.

3.2.3 Objective Graph Layer

The focus is placed on competencies in literacy linking macro level educational goals with particular teaching practices such as: knowledge learning objectives (to master the structure and adjustment methods of a spectrometer); professional ability objectives (possessing the ability to adjust optical instruments and process data) and ideological and political education objectives (cultivate a rigorous, truth-seeking scientific attitude).

3.3 AI Course Vertical Model: Lightweight Technical Path

3.3.1 Model Selection Strategy

Instead of using "large model + general knowledge" we chose the way of "lightweight model + domain knowledge". A 4-bit quantized open source model (e.g., Qwen2-7B or Phi-3) is selected as our basic inference engine which dramatically reduce its requirement in running on existing servers.

3.3.2 RAG Architecture Implementation

The interface was built using Streamlit in the front end; we use the LangChain framework connecting the Chroma vector database and the local large model for the back end. Workflow of the system: user question -> vector retrieval (recall relevant document fragments), context concatenation (combine retrieval results with user question together to form a prompt), model generation (answer according to the limited context), source annotation (return answer and cite sources).

3.3.3 Three-Level Response Strategy

Like Meng Yakun et al., our approach consists of a three level response mechanism as follows: (1) matching with the Q&A repository maintained by administrators; otherwise (2) generating a response from knowledge base via the AI course vertical model; or (3) supplementing by connecting to the cloud-based large model so that all questions are answered reliably.

4. Smart Teaching Model Design

4.1 Reconstruction of the “Human-AI Collaboration” Teaching Process

This study designed a human-AI collaborative teaching model covering the entire process of “preview—operation—report” (as shown in Figure 2):

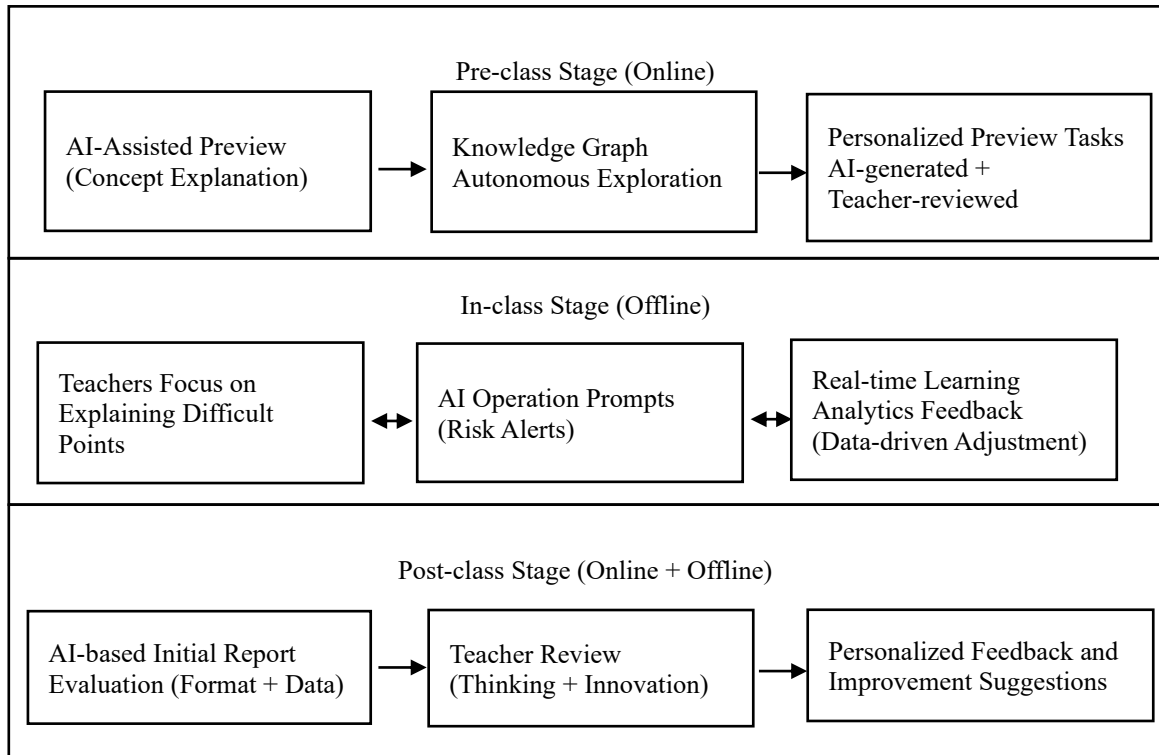


Figure 2 “Human-AI Collaboration” Physics Experiment Teaching Process

Pre-class: Students autonomously preview with an AI-powered Intelligent Learning Companion displaying the logical relationship between experimental principles, instrument structure and operation procedure based on the Knowledge Graph, marking weak points pushing relevant micro-lectures automatically. In-class: Teachers explain common difficult points according to learning analytics data; students are able to ask about operating procedures anytime by the AI which gives immediate prompts and annotate sources and actively push safety warnings for high-risk operations; teachers monitor the progress and problem distribution via the platform and dynamically adjust their teaching strategy. Post-class: First check the experiment report (data completeness, calculation standardization, the reasonableness of error analysis) giving a preliminary score and improvement suggestions from the AI followed by teacher's reviewing focus on scientific thinking, innovative awareness and problem analysis ability forming a final evaluation.

4.2 Diversified Intelligent Evaluation System

Based on Chen Hongzhang's idea about reshaping the evaluation system, we build a diversified intelligent evaluation system covering "process + outcome": Evaluation subject: Establishing a tripartite structure of "teacher evaluation—student evaluation—AI evaluation" in which AI gathers process data for preliminary analysis; Students conduct their own or peer evaluations but teachers make final judgments. Evaluation indicator: Adopting multidimensional quantitative standards (shown as Table 1).

Table 1: Evaluation System

Evaluation Dimensions	Specific Indicators			Data Collection Methods
Cognitive Ability	Knowledge Analysis	Understanding, Innovative Thinking	Problem	Knowledge Graph interaction traces, quiz scores
Practical Ability	Standardized Operation, Instrument Adjustment	Data Processing	Processing, Adjustment	Operation video analysis, report quality evaluation
Emotional Attitude	Learning Awareness, Scientific Attitude	Engagement, Collaborative	Collaborative	Platform dwell time, discussion participation

Values	Academic Integrity, Safety Awareness, Craftsmanship Spirit	Report originality detection, safety operation records
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For evaluation methods: Acquire the behavior of node visit frequency, interaction depth and operation sequence in real time; build a three-dimensional learner profile that changes from "single exam determines success or failure" to "full-cycle growth record"; For evaluation results: Provide personalized report with ability radar chart, knowledge mastery heatmap, learning path trajectory, improvement suggestion which is a basis for teachers' precise intervention and students' autonomous adjustment.

4.3 Transformation of Teacher Roles and Reconstruction of Competencies

Transformed teachers by means of AI empowerment: From being transmitters of knowledge to designing AI work objectives and learning workflows; from being experienced judges to becoming data-driven decision-makers (achieving precise teaching via learning analytics reports) or from being sole lecturers to become human-AI collaborators (mastering teaching skills for collaborating with AI and setting the boundaries between AI responsibilities, teacher intervention, and students' critical use).

5. Key Issues and Solutions

5.1 Low-Cost Technical Path

We use "4-bit quantization + 7B lightweight model + LangChain-Chroma open-source stack" so that our current CPU servers can handle one user every 30 seconds (optimizing with multi-GPU parallelism or request queues in case of concurrency).

5.2 Knowledge Accuracy and Controllability

We design a triple safeguard in our work: restricting the retrieval scope to textbooks and reviewed materials; prompting users to answer from given materials (insufficient? guide user to consult teachers); annotate answers with sources, support for feedback and update of Q&A repository by teacher review.

5.3 Data Security and Privacy Protection

We run locally, storing our data on campus servers; we anonymize interaction logs (no identity info); we establish tiered access permissions to use data only for teaching improvement.

5.4 Risk of Students' Thinking Dependence

We have designed a human-AI dialectical assessment in our study, which adds "AI Use Reflection" component and performs periodic assessments without any AI assistance guided by Question Graph: from seeking answers to exploring principles.

6. Discussion: Limitations and Prospects

6.1 Research Positioning and the Preliminary Nature of Results

We are proposing no "mature solution" that we have tested with a large sample but a "feasible technical blueprint". Our current test data of 39 students serve us for functional usability verification. Preliminary results (increased interaction frequency and decreased error rate), showing an auxiliary role of our system in regards to standardized prompts and format validation. Behavioral changes may lead to long-term competency improvement which needs to be tracked longitudinally and verified by controlled experiments.

6.2 Clarification of the Essence of the Technical Route

RAG system is basically "a domain knowledge retrieval and reorganization tool". Limitations for dealing with the operational, intuitive and error sensitive parts of physics experiments: reconstructing the logic of the Knowledge Graph, making a distinction between three types of nodes ("instrument

operation", "physical principles" and "error propagation"); substituting "large model generalist" by "small model + high-quality repository"; giving up generalization ability but achieving 92% test accuracy (within the syllabus domain).

6.3 Applicable Scope of the “Low-Cost” Paradigm

"without adding hardware": without buying dedicated AI accelerator cards. Uses CPU servers, async queue (response time is from 30s to 2 mins), which can be used in pre-class preview or after class initial evaluation but doesn't support 40 people at a time for real-time interaction.

6.4 Response to the Risk of “Cognitive Laziness”

Three mechanisms: Answer traceability forces you to look at the original text; The AI questioning log requires that you submit your error records (failure to identify limitations will lead to point deductions); Socratic questions focus on asking about raw data/principles, not outputting answers.

6.5 Scalability and Future Plans

The decoupling of the open-source technology stack and the knowledge base gives the architecture the potential to migrate to disciplines such as chemistry and biology. Future plans include:

- a. designing a quasi-experimental study with a control group;
- b. collaborating with 2 – 3 local colleges and universities for multi-site validation;
- c. exploring the combination of local models with cloud-based code interpreters to support automated error fitting.

7. Conclusion

According to "lightweight, low-cost, and highly available", we lay down a theory base and practice path for AI-empowered university physics experiment courses: Propose a three-in-one architecture of "Foundational Layer—Model Layer—Application Layer" that achieves controllable costs and data security by localization deployment; Design a human-AI collaboration model of "AI-Assisted Preview—Teacher-Focused Explanation—AI-Based Initial Evaluation + Teacher Review" forms a closed loop of "Teaching – Learning – Management – Evaluation – Testing"; Construct a "three-graph" vertical domain knowledge system which effectively suppresses the "hallucinations" of general large models; Verify the feasibility of an "accessible" path to provide a replicable model for local colleges and universities with limited funding and serves as a reference for the intelligent transformation of other basic experiment courses.

Fund Projects

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