

# Reconstruction and Practice of AI-Empowered Training Models for Electronic Information Engineering Professional Master's Students

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**Abstract:** To address the insufficient interdisciplinary integration, research computing bottlenecks, and low industrial adaptability in the training of Electronic Information Engineering professional master's students, this project leveraged the first-level discipline doctoral program in Physics to systematically reform the AI-empowered training model. Following a trinity pathway of "structural optimization, intelligent empowerment, and mechanism innovation," the study constructed a cross-curricular knowledge-capability graph and developed a central agent teaching platform. With the "Optoelectronic Engineering" and "Communication Engineering" tracks as pilot cases, we collected over 1,000 hours of controlled experimental data. The results demonstrate that the experimental group (AI-empowered) significantly outperformed the control group in terms of course objective attainment, research training efficiency, and practical innovation capabilities. Furthermore, the core value of AI empowerment lies in improving the "process quality" and "high-order outputs" of learning, rather than merely boosting test scores. This project validates the effectiveness of the "Physics Foundation—AI Empowerment—Engineering Application" integration framework, providing a replicable model for the reform of engineering professional degree graduate education in regional universities.

**Keywords:** Artificial Intelligence; Electronic Information Engineering; Professional Master's Degree; Training Model; Knowledge Graph; Central Agent; Collaborative Education.

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## 1. Introduction

The inspiration of AI deep learning by physics disciplines—including classical mechanics, electromagnetism, statistical physics, and quantum mechanics—and the application of AI in science and education have attracted considerable attention from scholars [1-3]. Rather than addressing whether to adopt AI, this study commenced with three pragmatic core questions: (1) how to substantively integrate AI technologies into the professional teaching chain to circumvent the incongruity—a superficial juxtaposition of AI and disciplinary instruction; (2) how to effectively translate the foundational disciplinary strengths of the Physics doctoral program into the innovative problem-solving capacities of engineering professional master's students; and (3) how to leverage regional industrial resources to remedy the deficiencies in practical platforms and industry engagement. These questions directly target the four predominant pain points in current professional master's training: lagging training objectives, insufficient interdisciplinary curriculum integration, slow renewal of practical platforms, and inadequate cultivation of innovative capabilities. To address these issues, the project adopted a cyclical action-research paradigm—"design, implementation, evaluation, and iteration"—and advanced simultaneously along four strands: curriculum system, research training, practical platform, and teacher development. The study involved 60 professional master's students majoring in Electronic Information Engineering (with concentrations in Optoelectronic Engineering and Communication Engineering), who were divided into a Control Group (CG) and an AI-Empowered Group (EG) using a controlled

experimental method, with both groups taught by the same cohort of instructors to control for variables. For the curriculum system, a three-tiered curriculum matrix of "Basic Theory + AI Tools + Engineering Application" was reconstructed, piloted in the course Information Retrieval. In research training, AI-assisted literature review and acceleration of first-principles calculations were introduced. For the practical platform, a joint "AI + Photovoltaic Industry Application" laboratory was established. Regarding teacher development, AI literacy workshops were conducted to facilitate the transition of faculty from "technology adopters" to "instructional designers."

## 2. Research Design and Implementation

### 2.1. Research Implementation Process

The curriculum design team spearheaded the systematization of the knowledge framework across the course cluster, mapping out a cross-curricular knowledge-capability graph that spans core courses in optoelectronics and communication engineering. This graph delineates the competency hierarchy corresponding to each knowledge point—ranging from memory and comprehension to application and innovation—and identifies specific intervention points where AI can be enabling. Building upon this foundation, the technology development team established a three-tiered technical architecture comprising a knowledge graph layer, an intelligent agent algorithm layer, and an application interaction layer. To support subsequent hybrid experiments that integrate virtual and physical elements, an experimental digital twin terminal was deployed. A pivotal

decision at this stage was to reject the simplistic approach of merely adding an "AI course"; instead, AI capabilities were modularized and embedded directly into the competency chains of existing professional courses, thereby eliminating the disconnect between technology and instruction at its source.

Subsequently, the technology development team completed the development of Central Agent V1.0, integrating modules for AI-driven knowledge extraction, automated PPT generation, intelligent grading, and research trend analysis. Preliminary testing of V1.0 revealed two critical issues: insufficient accuracy of general-purpose large language models in handling specialized terminology in optoelectronics and communication engineering, and a pronounced tendency among graduate students toward "uncritical acceptance" of AI-generated content. The former was addressed through the construction of a domain-specific terminology database coupled with a local Retrieval-Augmented Generation (RAG) knowledge base; the latter prompted the immediate launch of a mandatory seminar on "AI Research Ethics and Critical Usage." This intervention proved crucial for safeguarding training quality in later stages.

During the instructional implementation phase, the AI group's traditional teaching was augmented with the central agent, AI teaching assistants, and smart classrooms, while the control group adhered to the original training scheme. Concurrently, two flagship initiatives were launched: first, leveraging the Information Retrieval curriculum resources from Nankai University, a blended "online-offline" teaching model was implemented, embedding the entire chain of "information literacy—retrieval proficiency—research competence—academic integrity"; second, the "AI + Photovoltaic Industry Application" laboratory became operational, focusing on cultivating "technology foresight" by providing graduate students with authentic scenarios for photovoltaic material design, device optimization, and industry case studies. In the project's finalization phase, the data analysis team synthesized over 1,000 hours of behavioral logs into a comparative teaching effectiveness report, confirming significant improvements in the AI group regarding literature processing efficiency, computational time consumption, and device optimization cycles. Based on these findings, the project management team formulated construction standards for the course cluster, and the technology development team iterated the system to V2.0, thereby accomplishing the transition from "pilot intervention" to "standardized institutionalization."

## 2.2. Key Research Findings

At the curriculum integration level, the application of machine learning to the prediction of optoelectronic material properties significantly accelerated the design iteration speed of graduate students in the Optoelectronic Materials and Devices course. Device parameter optimization, which previously relied on trial-and-error, could now rapidly converge to optimal ranges through neural network surrogate models. In the communication engineering track, deep learning was employed in simulation tasks such as channel estimation and resource allocation, enabling students to tackle engineering problems of realistic complexity within limited class hours. The underlying mechanism is that AI assumes the heavy burden of "search and fitting," allowing students to redirect their cognitive resources toward problem modeling and result interpretation. Questionnaire data on course

objective attainment revealed that the AI group significantly outperformed the control group in "complex engineering problem modeling" and "cross-disciplinary knowledge integration." Meanwhile, the study identified a critical boundary: AI yielded limited gains in "basic knowledge acquisition" but produced substantial improvements in "higher-order capabilities (design, optimization, innovation)." This suggests that reform efforts should target the advanced nodes of the competency map rather than using AI as a superficial substitute for foundational training.

At the research training level, the introduction of NLP-based literature screening and knowledge graph construction substantially reduced the time required to locate high-quality references, with particularly notable effects on foreign literature comprehension and preliminary investigations for first-principles calculations. The replacement of partial DFT calculations with neural network potentials (NNP), combined with high-throughput material screening, markedly compressed the "material-device" iteration cycle, providing theoretical acceleration for photovoltaic material and optoelectronic device research. However, data analysis also revealed risk signals: some students exhibited "uncritical acceptance" of AI-generated abstracts and "unverified use" of AI-generated code, while certain literature reviews displayed a tendency toward viewpoint homogenization. Consequently, the project team established "AI Research Ethics and Critical Verification" as a compulsory module and implemented process-oriented evaluation requirements mandating "traceability of AI-assisted traces." This finding clearly indicates that the core of AI-enabled research training lies not in "extensive usage" but in "traceable and defensible usage."

Process data from the controlled experiment delineated a distinct differential profile: the AI group demonstrated higher classroom interaction frequency, more timely responses to after-class inquiries, increasingly personalized learning paths, and more proactive academic early-warning interventions. Although the gap in final exam scores between the two groups was relatively modest, the AI group exhibited markedly superior performance in comprehensive design and innovative practice tasks. This demonstrates that the true value of AI empowerment resides in improving the "process quality" and "high-order outputs" of learning, rather than merely inflating test scores. For instructional management, this finding supports replacing single-outcome evaluations with "process data mining" and resonates with educational reform directives emphasizing "innovative assessment methods and problem-solving abilities." Furthermore, operational data from the "AI + Photovoltaic Industry Application" laboratory showed that incorporating authentic corporate cases into the classroom significantly enhanced graduate students' engineering problem-definition capabilities. Survey feedback also indicated an urgent regional demand for interdisciplinary engineering talent who "understand physical mechanisms, can utilize AI tools, and are capable of on-site field deployment." This further substantiates that the vitality of professional degree reform in regional universities lies in transforming local industrial scenarios into training resources.

An unexpectedly important finding was that faculty AI literacy itself constituted a bottleneck for reform implementation. The project revealed that the degree of "teaching-research-industry" synergy among instructors directly determined whether AI tools could be effectively embedded into curricula. Some faculty members initially

exhibited "technological apprehension," struggling to translate AI capabilities into instructional design. The project team facilitated faculty role transformation through workshops and university-industry co-development programs. Practice has proven that faculty development is not merely a supporting element of reform but an integral component thereof; instructors' curriculum redesign capabilities directly determine the empowerment ceiling of the technical platform.

### 2.3. Research Conclusion

Synthesizing evidence from the four research strands, this project draws the following conclusions: (1) The three-tiered integration framework of "Physics Foundation—AI Empowerment—Engineering Application" is viable. The foundational theoretical advantages of the Physics doctoral program are effectively transformed into the innovative capabilities of engineering professional master's students through AI as a "catalytic binder," overcoming the fragmentation between basic and applied disciplines. (2) The value of AI empowerment concentrates on higher-order capabilities and process quality. Reform should focus on advanced nodes such as complex engineering problem modeling, research acceleration, and personalized learning, replacing singular outcome assessments with process-oriented, multi-dimensional evaluations. (3) "Regional resource input coupled with application scenario implementation" constitutes an effective pathway for reform in regional universities. Inter-university co-construction of high-quality courses and "AI + Photovoltaic" joint laboratories enable the trans-regional transformation of premium resources into local training capacities, providing talent support for the autonomous region's new energy industry upgrading. (4) "AI ethics and critical usage" must advance in parallel with tool empowerment. Unconstrained AI empowerment risks eroding academic originality; process traceability should be established as a fundamental requirement for AI-assisted research. (5) Faculty AI literacy and collaborative education mechanisms are the decisive variables in reform. Technical platforms are merely carriers; it is the depth of instructors' curriculum redesign capabilities and industry-academia linkages that ultimately determine reform efficacy.

## 3. Summary

Leveraging artificial intelligence as a catalyst, this project has initiated a systematic reconstruction of the professional degree graduate training system. The study demonstrates that, grounded in the profound foundation of the Physics doctoral program, regional universities are fully capable of cultivating high-quality, innovative applied talents who possess a deep understanding of underlying mechanisms, proficiency in advanced tools, and the adaptability to operate effectively in industrial scenarios—provided that AI empowers curriculum design, research training, practical platforms, and faculty development in an integrated manner. This reform practice not only addresses the technical demands of next-generation engineering education but also provides a replicable and iteratively refinable "INNU Model" for peer institutions in similar regional contexts, thereby offering robust talent support and intellectual contributions to the advancement of the electronic information and new energy industries.

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