Construction of Innovative Training and Evaluation Model for Generative AI Industrial Application in Engineering General Education

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Abstract. With the in-depth development of Industry 4.0, Generative AI has become a key technology driving the transformation towards smart manufacturing. However, current general AI education in engineering generally faces pain points such as "technology suspension, disconnection between production and education," and a single evaluation dimension. This paper proposes an innovative teaching paradigm for the course "Generative AI Industrial Application Training." This paradigm constructs a progressive training module design logic, from virtual simulation to physical production line joint debugging, and then to full-scenario coverage, to solve the engineering deployment challenges in complex industrial scenarios. Furthermore, this paper innovatively proposes a multi-dimensional capability evaluation framework based on the OBE-CDIO concept, deeply integrating process evaluation with student capability matrix portraits. This model demonstrates high replicability through the decomposition of lightweight application scenarios and collaborative sharing of open-source resources, providing a highly promotable new educational paradigm for engineering and technical talent cultivation in the context of new engineering.

Keywords: Generative AI, engineering education, virtual-real integrated training, multi-dimensional ability evaluation, OBE-CDIO, process evaluation.

1 Introduction

In the wave of digital transformation, large language models (LLMs) and multimodal generation technology are profoundly reshaping the production processes, mechanical design, and operation and maintenance paradigms of modern industries [1]-[3]. The evolution towards the industry 5.0 paradigm requires operational processes to not only exhibit high levels of automation but also achieve intelligent management through human-machine collaboration, which has been widely validated in digital twin-driven intelligent manufacturing, laser welding defect monitoring, and product service supply chain optimization [4]-[7]. Furthermore, the extension of distributed machine learning and intelligent analysis technology in fields such as healthcare, nanoscience, carbon

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emission monitoring, and metaverse privacy protection further highlights the core position of artificial intelligence technology in complex engineering environments and sustainable development [8]-[11]. However, traditional engineering education, when faced with the explosive evolution of generative AI, often remains limited to purely algorithmic theoretical derivation or single cloud-based code execution, lacking effective integration with real-world intelligent manufacturing scenarios [12]. Although traditional Outcome-Based Education (OBE) and the CDIO (Conceive-Design-Implement-Operate) concept provide a systematic engineering education framework, they face challenges such as single-dimensional curriculum evaluation and a disconnect between industry and academia when dealing with highly dynamic AI technology practices [13]-[14]. Students find it difficult to transform technologies like "prompt engineering" from textbooks into engineering capabilities capable of solving practical problems on the industrial site.

In order to addressing structural issues in existing AI-based education, such as insufficient industry-education integration, limited teaching resources, and single-dimensional evaluation, this study proposes a reconstructed practical teaching and evaluation paradigm based on the teaching practices of modern industrial colleges. This paradigm is grounded in AI application skills, avoids complex underlying algorithmic derivation, and deeply integrates the entire chain of "product design-process optimization-production operation and maintenance". Through a dual-loop teaching method interweaving virtual and reality and a process-driven four-dimensional capability portrait evaluation system, this model aims to cultivate high-quality engineering and technical talents with interdisciplinary problem-solving abilities, systematic engineering thinking, and strict data ethics awareness.

2 Reform and Reconstruction of Progressive Training Teaching Mode

In order to bridge the gap between laboratory and industrial field applications, this study designed a lightweight industry academia integration path of "demand penetration process penetration achievement penetration". In fact, the core of the reality training mode lies in the step-by-step leap from virtual to physical objects.

2.1 Virtual-Physical Dual Loop Architecture

This paradigm pioneered a dual platform collaborative mechanism of cloud workshop+physics training. Virtual loop (cloud-based verification): In response to the high computational threshold and complex local environment configuration issues in traditional practical training courses, this model relies on an online open-source AI application development platform to deploy a cloud-based teaching environment. Students complete online fine-tuning and API call testing of multimodal models in this environment, achieving low-cost concept generation and scheme validation. Real environment (physical equipment integration): After virtual verification is passed, the training enters the real environment stage. Based on the real production line equipment of the Intelligent Industry College shown in Fig.1 (accounting for 40% of the core class hours), students need to perform joint debugging and testing of AI models generated in the cloud with physical devices. For schools with limited budgets, there are two low-cost alternatives to the physical production line: 1) Modular training equipment that can simulate the core functions of the industrial production line, such as material transportation, simple assembly, and basic detection. 2) Hardware in the loop (HIL) simulator, which can build a virtual-physical hybrid simulation environment, accurately simulating the dynamic characteristics of industrial equipment and the interaction process with the artificial intelligence model. These two schemes are compatible with the original training module design and can be flexibly selected according to the school's resource conditions. This dual loop verification of "virtual simulation → physical training" ensures the usability and robustness of the model in the physical world.

Fig. 1. Laboratory training equipment.

As for the teaching staff, the school enterprise cooperation teaching is adopted (the ratio of school enterprise engineers and university teachers with more than 3 years of GenAI experience is 1:1, and the internal training of teachers will be carried out regularly.

The generative AI part of this course covers AI text generation, image generation, code generation and other modes, including: 1) PLC code generation. 2) Synthetic data generation of visual model. 3) Part disassembly drawing generation design. 4) Process improvement scheme design. 5) Principle-explanation PPT design. In addition, as generative AI hallucinations may pose security risks in physical production line deployment, this course has a security protection and risk mitigation module, which has three parts: 1) Security protection teaching: guide students to design AI model access management, real-time output monitoring, and an emergency stop mechanism with physical equipment to prevent unsafe operations from model errors. 2) Deterministic backup training: teach students to design backup control strategies that can be quickly activated when the generative AI model outputs abnormally. 3) Risk mitigation practice: let students conduct practices like risk identification, emergency disposal, and root-cause analysis through simulating fault scenarios.

To avoid hollowing out the training content, the design of the training module adopts a top-down reverse disassembly strategy. By closely integrating with regional leading industrial clusters, the training focuses on the key issues, such as intelligent generation of process files and intelligent adjustment of process parameters. More than ten lightweight standard training modules have been developed.

2.2 Step by Step Promotion of Three-Level Ability Cultivation

The entire practical training teaching is divided into three progressive cognitive steps:

1) Basic cognitive layer: focuses on large model interaction and engineering deployment (including prompt word engineering, lightweight fine-tuning, etc.).

2) Practical application layer: Advanced development of multimodal generation systems, such as industrial design workflow reconstruction and agent construction.

3) Industrial innovation layer: Challenge cross scenario solution design, requiring students to collaborate with teams to complete comprehensive projects similar to the AI quality inspection+process optimization linkage system, connecting the entire chain of requirement analysis-solution design-verification iteration.

3 Innovation of Student Ability Evaluation Methods

Traditional engineering course evaluation mainly focuses on static code testing at the end of the semester, which cannot comprehensively measure students' comprehensive literacy in complex engineering environments. This model innovatively reconstructs the evaluation system.

The evaluation mechanism has shifted from result judgment to process monitoring. By deploying a teaching analysis platform, key technical indicators during the training process (such as API call accuracy, model inference latency, and other hard indicators) are tracked and recorded in real-time. In addition, the project adopts a dual evaluation mechanism, with enterprise engineers or external industry experts deeply involved in 50% of the practical course scoring process, focusing on rigorous engineering verification of the industrial adaptability of the solution from dimensions such as industrial cost, system compatibility, and solution maintainability.

In the era of AI, learners must establish clear technology proxies and compliance boundaries. Therefore, this article proposes a four-dimensional evaluation system for AI ability, as shown in Fig. 2. This framework abandons the single dimensional score evaluation and generates an exclusive ability matrix portrait for each student, which is based on the following four core dimensions:

1) Technical proficiency: Test students' mastery of API call specifications, model fine-tuning logic, and deployment architecture.

2) Ethical & normative standards: Emphasize data compliance and privacy protection. Include content credibility verification, privacy data cleaning, and industrial desensitization processing standards in the assessment. For example, setting up a "data security attack and defense drill" in the data preprocessing stage to test students' com-

pliance with data privacy regulations (such as GDPR and other international standards) through hard indicators.

3) Collaborative innovation: Evaluate students' performance in human-computer collaboration process design, multimodal information fusion, and team cross role collaboration.

4) Engineering application: The ability to design systematic solutions for core testing, as well as the scene matching performance of models in the face of real industrial noise.

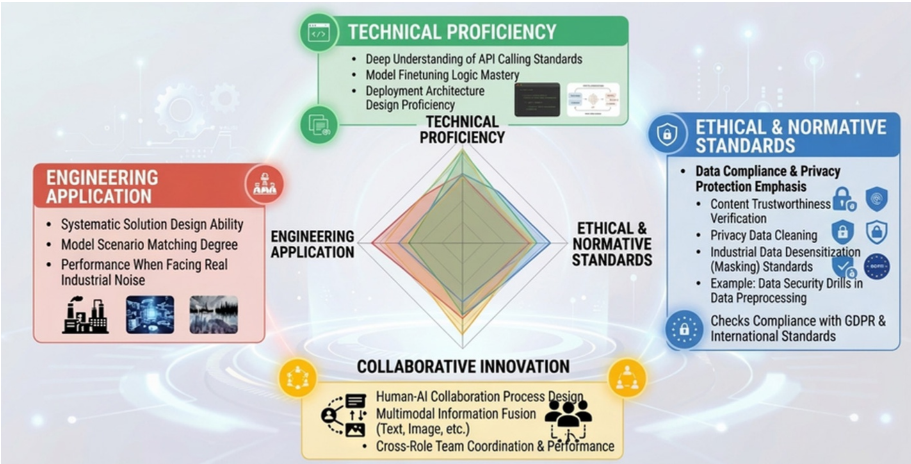

Fig. 2. Four-dimensional evaluation system for AI ability.

This matrix style portrait evaluation not only horizontally links technical scoring with engineering ethics standards, but also provides data support for personalized teaching optimization in the future.

This teaching paradigm prioritizes replicability from the beginning of its design and has the following characteristics:

3.1 Lightweight cloud architecture breaks down hardware barriers

By deploying a development environment on the browser side, supporting online fine-tuning testing and outputting reusable industrial scene code templates, the hardware computing power funding threshold for universities to carry out advanced AI practical teaching has been greatly reduced. This combination of cloud lightweight+physical interface modularization enables this model to quickly radiate to other universities lacking large supercomputing centers.

3.2 Case Study on Mass Creation and Open-Source Ecological Construction

The model promotes the case-co-creation mechanism, collaborates with multiple universities and industry enterprises to jointly establish an industrial scene template library covering a large number of standardized prompt words and an open-source resource pool of real industrial cases. This co construction and sharing mechanism not only feeds back teaching, but also promotes cross institutional curriculum frequency and resource standardization.

3.3 Shaping Engineering Thinking for General Industry Needs

This paradigm introduces a localized deployment framework and a data security sandbox mechanism to guide students in mastering the underlying application capabilities that are independent of specific cloud service providers, cultivating technical adaptability to solve complex engineering environment limitations. This has provided modern engineering and technical talents with high-level cognition, rigorous compliance awareness, and solid practical abilities for a wide range of industries such as modern manufacturing and software engineering.

4 Conclusion

The innovative teaching mode of the generative AI industrial application training course constructed in this study fundamentally solves the dilemma of traditional general education course technology being detached from the scene. Through the dual loop progressive teaching architecture of "virtual simulation → physics training" and the four-dimensional ability matrix evaluation system with multi-party participation, this model not only solidifies students' AI underlying application skills, but also reshapes their systematic engineering thinking in dealing with complex industrial problems and data compliance challenges. Its lightweight cloud deployment strategy and open-source case ecosystem ensure the strong replicability and promotional value of this model in a wide range of international engineering education fields.

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