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Research on Mechanisms and Pathways of Generative Artificial Intelligence Empowering Intelligent Manufacturing Curriculum Teaching Reform

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Abstract: *Objective:* Focusing on the adaptability contradiction between talent cultivation in the intelligent manufacturing field and industrial demands, this paper proposes a curriculum teaching reform plan with generative artificial intelligence (GAI) technology as the core driving force. By constructing a "dual-loop driving" teaching model (collaboration between the cognitive construction loop and the technology empowerment loop) and an AI-enhanced C2D2IO framework, the theoretical mechanism of human-machine collaborative teaching is systematically explored. Based on the "three-stage nine-step" teaching method, the curriculum system is reconstructed, and a teaching system integrating digital twin and intelligent diagnosis functions is developed. Practical paths, including industrial fault case library construction, cloud-based resource sharing, and enterprise projects entering the classroom, are formed. Finally, the reform effect is verified through the "four-dimensional radar evaluation model" (learning satisfaction, competency achievement, industrial adaptability, innovation contribution). Research shows that this plan can shorten the post adaptation period of graduates to 2.8 months, increase the proportion of real enterprise projects entering the classroom to 60%, and improve the score of complex engineering problem-solving ability by 18.2 points. The research results can provide a theoretical reference and a practical paradigm for the digital transformation of engineering education in the background of emerging engineering education.
Keywords: Generative artificial intelligence; Intelligent manufacturing; Curriculum teaching reform; Human-machine collaborative teaching

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1. Introduction

1.1. Research background

Against the backdrop of the global manufacturing industry's transformation toward intelligent manufacturing, traditional engineering education models face challenges such as outdated knowledge systems, insufficient industry-education integration (a collaborative model aligning talent training with industrial needs), and weak cultivation of innovative capabilities [1–3]. Generative Artificial Intelligence (GAI), as a core driver of technological change, has not only reshaped industrial R&D processes, production logics, and organizational forms [4] but also put forward new requirements for the teaching paradigms, talent cultivation goals, and evaluation systems of higher education. Hao et al. pointed out that GAI is a key force driving the paradigm transformation of research universities and realizing the coordinated development of independent scientific and technological innovation and talent cultivation [5]; its in-depth application in education has become an inevitable choice to respond to national strategic needs and consolidate core competitiveness. Hao et al.'s research further noted that GAI can construct new academic research communities, build breakthrough innovative knowledge systems, strengthen systematic interdisciplinary construction, create efficient achievement transformation ecological chains, and promote in-depth integration of industry, education, and research; however, this process has quietly spawned multiple risks such as "innovation traps", "scientific research distortion", "academic colonization", and "academic misconduct", which adversely affect the overall innovation efficiency of high-level research universities, global academic credibility, the dominant position of knowledge innovation subjects, and the cultivation of top innovative talents. To address these issues, high-level research universities should continuously regulate algorithmic power, provide algorithmic support combining academic autonomy and independent innovation; conduct full-cycle data governance to lay a solid foundation for data security in disruptive technological research; build a technological governance community to strengthen the technological leadership of organized scientific research; and establish ethical norms for human-machine collaboration to cultivate compound digital intelligent top innovative talents.

Meanwhile, the complexity and practicality of the intelligent manufacturing course teaching urgently require technological empowerment to break through traditional teaching bottlenecks. Tian et al. found through a systematic literature review that feedback mechanisms of educational agents (e.g., facial expressions, human-like voices) can significantly enhance learning motivation and social presence [6–8], while Zhong et al.'s research showed that question strategies and prompt framework design for reasoning large models directly affect learning outcomes [9]. This provides a theoretical basis and practical inspiration for the application of GAI in intelligent manufacturing courses. However, current intelligent manufacturing course teaching still faces issues such as "shallow dependence" on technical tools and a lack of systematic human-machine collaboration mechanisms[4,10,11], so there is an urgent need to construct a new teaching paradigm adapted to intelligent manufacturing needs.

1.2. Research status

World-class universities have taken the lead in exploring the integration of GAI and higher education. Zhou et al. pointed out that some universities have issued detection regulations to ensure teaching quality in response to the impact of AI-generated Content (AIGC) on academic originality [12]; however, Guo's research showed that the AIGC identification system faces technical implementation difficulties and subject responsibility dilemmas in practice [6], reflecting the complexity of technological governance. Zhou et al.'s research further noted that effectively distinguishing between human and machine differences, regarding AIGC use as ghostwriting, recognizing the separation between operators and AIGC, and worrying about technology's substitution for human capabilities collectively constitute the premise for the emergence of AIGC detection regulations. However, under critical examination of theory and practice, the effectiveness of technical discrimination is questionable; there are misunderstandings in the ghostwriting assumption, the consensus on human-machine separation is shaken, and the limitations of the capability substitution assumption challenge these premises. Thus, universities need to shift from AIGC detection to substantive paper content review, from focusing on ghostwriting to process-based capability assessment, strengthen the consistency of academic evaluation in process and result dimensions, and commit to cultivating students' comprehensive literacy and innovative capabilities to adapt to changing times.

Jiang et al. found through analyzing policies of the top 100 global universities that foreign institutions generally adopt a "support and constraint" strategy: at the teaching level, they enhance effectiveness by providing "GenAI toolboxes" before class, guiding GenAI-assisted teaching during class, and conducting precise assessment with GenAI after class; at the management level, they implement hierarchical authorization and integrity declarations to prevent academic misconduct [13]. In addition, Mackenzie's research pointed out that the rapid development of GAI has brought both technological breakthroughs and concerns about ethics and employment [8], which provides a warning for risk prevention in intelligent manufacturing course reform. Mackenzie's research also mentioned that in 1950, computer pioneer Alan Turing proposed an AI test named after him: an AI-equipped machine should be able to chat with humans and convince them it was human. While the Turing test is not an adequate definition of AI, it has long been regarded as an important milestone.

Domestic scholars have carried out multi-dimensional explorations on GAI empowering education. Su et al. found through recruitment information analysis that talent demand in the GAI field focuses on model R&D, product development, and team management, emphasizing capabilities such as algorithm programming, data processing, and cloud computing platform experience [14], which provides an industry reference for intelligent manufacturing course capability cultivation goals. Su et al.'s research further noted that the main job responsibilities of GAI positions include seven aspects: cutting-edge research and knowledge sharing, model and algorithm R&D, customer demand analysis and satisfaction, generative product R&D and management, scalable solution development and implementation, team management and leadership, and strategic planning. Capability requirements include basic GAI knowledge, algorithm and programming skills, software engineering and architecture, data processing, cloud computing platform experience, product development, as well as personal qualities such as communication, leadership, problem-solving, and adaptability. Additionally, academic achievements, entrepreneurial experience, and mindset are required.

Zhong et al.'s experimental research showed that the combination of the "two-stage three-link" question strategy and non-visual reasoning is more conducive to improving students' innovative capabilities [9], providing empirical evidence for course teaching method design. In the field of engineering education, Yan constructed an embodied intelligence-empowered experimental teaching system for human factors engineering, using humanoid robots to simulate complex human-machine interaction scenarios and GAI to build dynamic task contexts [15]; its "theory-practice-capability" closed-loop mechanism has important reference significance for intelligent manufacturing courses. Yan's research further noted that this system is based on "intelligent technology as the foundation, human factors theory as the soul, and capability cultivation as the core", using large models to realize multi-modal interaction and promote experimental teaching toward immersion and intelligence. The system focuses on four core links (perception-interaction-decision-execution), integrates multi-modal perception and human-machine interaction technologies, and forms a closed-loop cultivation mechanism. Practice shows that this system effectively improves students' comprehensive capabilities in human factors design and intelligent technology application, and enhances their awareness of engineering innovation and ethical responsibility, providing a contextualized, intelligent, and systematic new paradigm for human factors engineering experimental teaching.

Chen proposed that collaborative thinking with AI can reshape human thinking processes and construct new thinking loops [16], which provides theoretical support for the collaborative mechanism between the cognitive construction loop and technology empowerment loop in the "dual-loop driving" teaching model. Chen's research further noted that collaborative thinking with AI can reshape thinking processes, construct new thinking loops and information flow ways; AI can become a thinking partner, and humans can learn new knowledge organization methods, develop new thinking, and improve capabilities through collaboration with AI—this process itself is a new learning process.

However, existing research still has deficiencies: First, at the theoretical level, there is a lack of an AI intervention logical framework for intelligent manufacturing courses. For example, Liu et al. pointed out that educational knowledge transformation faces dilemmas such as difficulty in externalizing tacit knowledge and interdisciplinary integration [17], so there is an urgent need to clarify AI's mechanism in links such as "collaborative conception, virtual debugging, and intelligent operation and maintenance". Liu et al.'s research further noted that current educational knowledge transformation faces multiple dilemmas: difficulty in externalizing tacit knowledge, scaling innovative achievements, grasping knowledge system complexity, and interdisciplinary integration. Large model technology provides an opportunity to solve these dilemmas. This study systematically analyzes core challenges of educational knowledge transformation, demonstrates the applicability of large models, and constructs a large model-supported knowledge transformation path framework based on implementation science. The framework takes evidence integration, adaptive transformation, implementation guarantee, innovation diffusion, and ethical considerations as core elements, clarifying the application of large models in each link.

Second, at the practical level, Mo et al. pointed out that mechanical engineering graduate education has problems such as insufficient industry-education integration and weak innovative capability cultivation [1]. Mo et al.'s research further noted that the intelligent manufacturing background puts forward new requirements for the knowledge structure and ability literacy of mechanical engineering graduates. This paper analyzes deficiencies in China's mechanical engineering graduate education in training objectives, curriculum system, teaching model, practice links, tutor team, and evaluation mechanism (e.g., insufficient industry-education integration, weak innovation cultivation, outdated knowledge systems). Combining advanced concepts such as competency-based education, industry-education integration, and cutting-edge interdisciplinary, this paper constructs a reform path with "cutting-edge leadership, interdisciplinary integration, practice-driven, and innovation empowerment" as the core, including: defining talent training objectives in the intelligent manufacturing context; reconstructing a modular, cutting-edge, and interdisciplinary curriculum system; deepening the reform of the "project-through" teaching model; building a multi-level open innovation practice platform; constructing a diversified collaborative tutor team; and establishing a comprehensive evaluation mechanism emphasizing both process and development.

By comparing vocational education experiences of Germany, the United States, and Japan, Zhang emphasized the need to strengthen school-enterprise cooperation and teaching model innovation [18], but a systematic curriculum reform path has not yet been formed. Zhang's research further noted that the global manufacturing industry is facing great changes brought by intelligent manufacturing technology; enterprises need new employees with good vocational education and provide lifelong learning opportunities for in-service employees. All countries generally believe that a strong vocational education and training system is essential to provide high-quality technical talents for manufacturing. Analyzing the experiences of Germany, the United States, and Japan—comparing their performance in employment rate, flexibility, and adaptability from the perspective of school-running subjects, their similarities and differences in industry leadership and school-enterprise cooperation from the perspective of scientific and technological innovation, and their innovations in teaching models and content from the perspective of teaching innovation—can provide reference for China's intelligent manufacturing talent cultivation [19–22].

In summary, GAI-empowered intelligent manufacturing course reform has become an important issue in engineering education. This study aims to construct a "dual-loop driving" teaching model and an AI-enhanced C2D2IO framework, develop a "three-stage nine-step" teaching method and a digital twin teaching system, explore practical paths and verify reform effects, and provide theoretical guidance and practical paradigms for promoting innovative development of intelligent manufacturing course teaching.

1.3. Research objectives and content

1.3.1. Research objectives

This study aims to systematically explore the theoretical mechanisms and practical paths of generative artificial intelligence (GAI) empowering intelligent manufacturing curriculum teaching reform. The specific objectives include:

(1) Constructing a "dual-loop driving" teaching model to reveal the internal interaction mechanism between GAI and human-machine collaborative teaching;

(2) Designing an AI-enhanced C2D2IO teaching framework and a "three-stage nine-step" teaching method, and developing a digital twin teaching system integrating digital twin and intelligent diagnosis functions;

(3) Exploring replicable practical paths, including implementation strategies for key links such as industrial fault case library construction, cloud-based resource sharing, and enterprise projects entering the classroom;

(4) Establishing a "four-dimensional radar evaluation model" to quantify the effect of teaching reform from four dimensions: learning satisfaction, competency achievement, industrial adaptability, and innovation contribution.

1.4. Research content

1.4.1. Theoretical mechanism construction level

Integrate constructivist learning theory and Industry 4.0 system theory to analyze the interaction mechanism between the cognitive construction loop and technology empowerment loop; based on the "Eight-Element System Model of Human-Intelligence Collaborative Teaching", define the role boundaries and interaction rules of teacher-AI-student tripartite subjects, and quantify the AI cognitive agency threshold (task complexity ≥ 0.65) and the core value domains of teachers.

1.4.2. Teaching model design level

Develop an AI-enhanced C2D2IO teaching framework, adding "collaborative conception" and "intelligent operation and maintenance" links to the traditional CDIO model; design a "three-stage nine-step" teaching method, dividing the teaching process into three stages: virtual simulation foundation, production line-level collaborative training, and engineering comprehensive application; support the development of a digital twin teaching system to achieve high-fidelity reproduction of over 85% of industrial scenarios.

1.4.3. Practical path exploration level

Construct an industrial typical fault case library covering more than 1200 fault scenarios, and establish a knowledge graph of "fault phenomenon - cause analysis - solution"; build a cloud-based intelligent teaching platform, adopting the "provincial overall planning + municipal sub-node" architecture; explore the mechanism of real enterprise projects entering the classroom to ensure that over 60% of core courses integrate real enterprise projects.

1.4.4. Effect evaluation and verification level

Construct a "four-dimensional radar evaluation model", using methods such as Likert 5-point scale, CMMM Level 5 standard, and text similarity analysis to measure teaching effects; select three universities of different types to carry out empirical research, and compare the learning effect differences between the experimental.

2. Theoretical basis of the "dual-loop driving" teaching model

2.1. Theoretical origin and core connotation

The "Dual-Loop Driving" teaching model is rooted in the deep integration of Constructivist Learning Theory and Industry 4.0 System Theory. Piaget's Cognitive Development Theory emphasizes that learning is an active knowledge construction process through the "assimilation-accommodation" mechanism, while Vygotsky's Sociocultural Theory highlights the core role of social interaction in the development of advanced psychological functions. This model expands the traditional "teacher-student binary interaction" into a "teacher-AI-student tripartite interaction", and achieves the trinity coupling of "learning process-technology tools-industrial demands" through dynamic collaboration between the Cognitive Construction Loop and Technology Empowerment Loop.

The Cognitive Construction Loop follows the path of "Embodied Experience → AI Reflection → Conceptual Abstraction → Active Experimentation": Students gain embodied experience of equipment operation (e.g., tool wear experiments in CNC machining centers) through digital twin systems; AI agents generate reflection reports (including operation deviation analysis and improvement suggestions) based on real-time data to guide students in abstracting process parameter optimization rules; students then verify improvement plans through active experiments. The Technology Empowerment Loop forms a closed loop of "Digital Twin → Intelligent Diagnosis → Dynamic Optimization → Knowledge Precipitation": Digital twin technology realizes real-time mapping between physical equipment and virtual models; intelligent diagnosis systems automate repetitive guidance tasks; dynamic optimization modules push personalized learning resources; knowledge precipitation converts optimization experiences into case libraries and knowledge graphs.

2.2. Diagram of the "dual-loop driving" teaching model

Figure 1 shows two nested circular structures: The inner circle is the Cognitive Construction Loop, labeled "Embodied Experience → AI Reflection → Conceptual Abstraction → Active Experimentation" with arrows connecting each link and typical case data (e.g., "error rate reduced by 43% in AI Reflection link"); the outer circle is the Technology Empowerment Loop, labeled "Digital Twin → Intelligent Diagnosis → Dynamic Optimization → Knowledge Precipitation" with each link corresponding to the inner circle and bidirectional arrows indicating data interaction. The core area is labeled "teacher-AI-student tripartite interaction" with different colors distinguishing the role boundaries of the three parties.

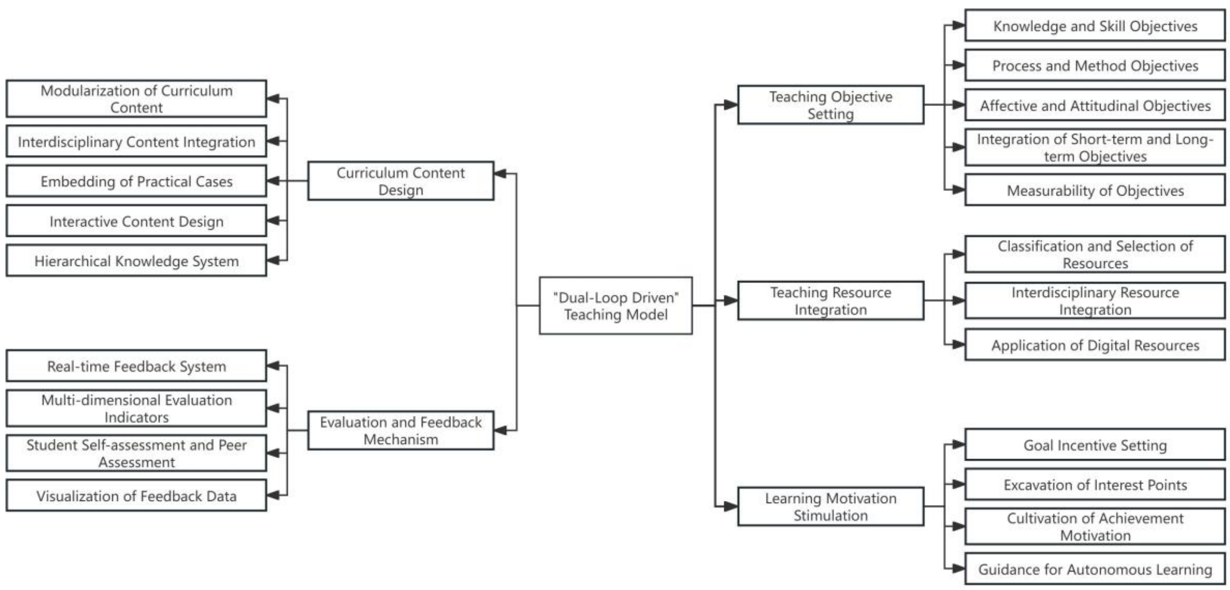

Figure 1. "Dual-loop driving" teaching model.This model achieves dynamic balance between knowledge construction and technology empowerment through collaboration between the Cognitive Construction Loop and Technology Empowerment Loop. The dual-loop coupling nodes include data middle platform sharing, goal coordination matrix, and resource reuse mechanism.

2.3. Coupling mechanism of dual-loop collaboration

The Cognitive Construction Loop and Technology Empowerment Loop achieve deep coupling through three mechanisms: "Data Interaction → Goal Coordination → Resource Sharing."

2.3.1. Data interaction mechanism

The data middle platform shares student operation data (e.g., error types, completion time) and teaching resource data (e.g., virtual scene parameters) in real time to form closed-loop regulation. For example, when students repeatedly make "robot path planning conflict" errors, the data middle platform pushes information to the dynamic optimization module to reduce virtual scene difficulty and push relevant micro-lesson videos.

2.3.2. Goal coordination mechanism

Based on the "ability-resource" mapping matrix, the horizontal dimension is core intelligent manufacturing capabilities (e.g., digital twin modeling) and the vertical dimension is teaching resource types (e.g., virtual scenes). Each cross-unit labels the contribution degree of resources to capabilities (e.g., "engine virtual disassembly and assembly" contributes 0.8 to "equipment operation capability").

2.3.3. Resource sharing mechanism:

Shared knowledge graphs and case libraries are used—for example, the "fault diagnosis knowledge graph" in the AI Reflection link of the Cognitive Construction Loop shares the same source as the knowledge base of the intelligent diagnosis system in the Technology Empowerment Loop, and is updated synchronously through version control. The "One-Base Dual-Loop" system of Hunan Vocational College of Science and Technology increased the resource reuse rate by 65% and reduced resource development cost by 40% through this mechanism.

2.4. Technical intervention logic of the AI-enhanced C2D2IO framework

2.4.1. Components and upgrade path of the framework

The AI-enhanced C2D2IO framework is an intelligent upgrade of the traditional CDIO model, adding "Co-creation" and "Intelligent Operation" links to form a five-stage closed loop of "Co-creation → Design → Virtual Debugging → Implementation → Intelligent Operation". The core tasks and AI intervention points of each link are as follows:

(1) Co-creation: Demand analysis, scheme design, multi-objective optimization. AI generates 3-5 preliminary schemes based on knowledge graphs and uses reinforcement learning algorithms to balance performance-cost-efficiency conflicts (e.g., aerodynamic performance and structural strength optimization of high-speed train heads).

(2) Design: 3D modeling, control logic design. AI assists in parametric modeling (e.g., automatic generation of PLC ladder diagrams) and performs conflict detection (e.g., mechanism motion interference check).

(3) Virtual Debugging: Virtual-real linkage control, fault injection. AI accelerates simulation (GPU parallel computing shortens debugging cycle by 70%), automatically finds errors and generates parameter optimization suggestions.

(4) Implementation: Physical equipment operation, data collection. AI provides operation guidance and anomaly warnings (e.g., real-time monitoring of equipment vibration data and early warning of potential faults).

(5) Intelligent Operation: Fault diagnosis, predictive maintenance. AI integrates multi-modal data (vibration, temperature) for fault diagnosis and predicts Remaining Useful Life (RUL) based on LSTM networks.

2.4.2. Design of the AI-enhanced C2D2IO framework

The AI-enhanced C2D2IO framework is an intelligent upgrade of the traditional CDIO engineering education model, forming a five-stage closed loop of "Co-creation → Design → Virtual Debugging → Implementation → Intelligent Operation" by adding "Co-creation" and "Intelligent Operation" links. Each stage deeply integrates core tasks with AI technology: In the Co-creation stage, preliminary schemes are generated based on knowledge graphs, and multi-objective optimization of performance, cost and efficiency is achieved through reinforcement learning algorithms; in the Design stage, automation of parametric modeling and conflict detection is realized, assisting in PLC ladder diagram generation and mechanism motion interference check; in the Virtual Debugging stage, simulation is accelerated by GPU parallel computing, and automatic error finding and parameter optimization suggestions are generated, shortening the debugging cycle by 70%; in the Implementation stage, real-time operation guidance and anomaly warnings are provided, and potential faults are predicted by monitoring equipment vibration data; in the Intelligent Operation stage, multi-modal data (vibration, temperature) are integrated for fault diagnosis, and Remaining Useful Life (RUL) is predicted based on LSTM networks. Stages are seamlessly connected through the data middle platform—for example, design schemes directly serve as input for virtual debugging, and optimized parameters from virtual debugging are fed back to physical operation in the Implementation stage, forming a complete technical closed loop.

The core breakthroughs of the framework lie in reconstructing the technical intervention logic of engineering education, upgrading AI from an auxiliary tool to a cognitive agent, and achieving efficiency leapfrogs in three key links:

(1) Scheme optimization: AI-generated multi-objective optimization schemes increase the balance efficiency of aerodynamic performance and structural strength of high-speed train heads by 40%;

(2) Virtual debugging: GPU acceleration and automatic error finding compress the traditional physical equipment-dependent debugging cycle from 2 weeks to 3 days;

(3) Intelligent operation: Multi-modal diagnosis models increase fault identification accuracy from 65% (traditional manual) to 92%. Practice verification shows that after framework implementation, the proportion of teachers' repetitive guidance tasks decreased from 45% to 20%, students' complex engineering problem-solving ability score increased by 18.2 points, the proportion of real enterprise projects entering the classroom reached 60%, and the post adaptation period shortened from 5.9 months to 2.8 months—fully reflecting the synergistic effect of

"technology empowerment → cognitive upgrade → industrial adaptation".

2.5. Role boundaries of teacher-ai-student tripartite interaction

2.5.1. Role positioning of tripartite subjects

(1) Teacher Role: Transforms from "knowledge transmitter" to "learning designer" (designs course modules and project tasks), "thinking guide" (guides high-order thinking and engineering ethics discussions), and "ethics mentor" (guides responsible use of AI technology).

(2) AI role: Acts as a "cognitive assistant" to automate 30%-45% of repetitive tasks (e.g., basic Q&A, homework correction); a "skill coach" to provide 24/7 virtual training guidance (e.g., real-time error correction in CNC programming); and a "resource steward" to recommend personalized learning paths (e.g., pushes cases based on ability portraits).

(3) Student role: Changes from "passive receiver" to "knowledge constructor" (actively explores digital twin scenes), "problem solver" (diagnoses industrial faults), and "innovative practitioner" (develops intelligent diagnosis tools).

2.5.2. Teacher-AI-Student Tripartite Interaction Mode

The teacher-AI-student tripartite interaction mode takes a triangular structure as the core framework, with three vertices corresponding to teachers, AI and students respectively. The three edge areas label three dynamic interaction modes: "Human-led, AI-assisted" (basic concept learning scenarios, AI agency degree < 0.4), "Human-AI Collaborative" (complex skill training scenarios, AI agency degree 0.4–0.65), and "AI-led, Human-assisted" (innovative practice scenarios, AI agency degree ≥ 0.65). Each mode area clarifies typical tasks and interaction rules: In the "Human-led, AI-assisted" mode, teachers lead teaching and AI provides standardized resources (e.g., 3D animation of equipment structure); in the "Human-AI Collaborative" mode, complex skill training is completed through human-machine division of labor (e.g., AI injects faults to train diagnostic capabilities, teachers guide analysis logic); in the "AI-led, Human-assisted" mode, AI deeply participates in innovative practice (e.g., generates optimization schemes based on knowledge graphs), and teachers focus on high-order thinking cultivation and engineering ethics guidance. This mode dynamically adjusts interaction relationships according to task complexity—when task complexity ≥ 0.65, AI undertakes main technical support, reducing teachers' repetitive guidance time by 45% and achieving precise adaptation of human-machine collaborative teaching.

3. Design and development of an intelligent manufacturing curriculum teaching model

3.1. Curriculum system reconstruction of the "three-stage nine-step" teaching method

3.1.1. Overall architecture of the teaching method

The "Three-Stage Nine-Step" Teaching Method divides the teaching process into three progressive stages: Virtual Simulation Foundation, Production Line Collaborative Training, and Engineering Comprehensive Application, each containing three implementation steps to form a closed-loop curriculum system.

(1) Virtual simulation foundation stage (35% of total class hours): Focuses on basic operation and programming skills of single equipment, with steps: *Equipment Cognition → Virtual Operation → Virtual-Real Verification*. Basic concepts are established through AI interactive explanation (e.g., 3D animation demonstration of equipment structure) and virtual disassembly training (e.g., disassembly of CNC machine tool spindle unit); programming training (e.g., PLC logic programming) is conducted in a virtual environment, with AI providing syntax checks and logic optimization suggestions; skill transfer is achieved via virtual-real linkage verification (comparison of machining results under the same parameters). Practice in a vocational college shows that this stage increased students' equipment structure cognition accuracy from 68% to 91%.

(2) Production line collaborative training stage (40% of total class hours): Cultivates multi-equipment collaboration and system debugging capabilities, with steps: *Production Line Planning → Virtual Debugging → Virtual-*

Real Linkage. Production line layout is designed based on enterprise needs (e.g., annual output of 100,000 auto parts production line), with AI providing optimization suggestions using the Systematic Layout Planning (SLP) method; control logic is debugged on the digital twin platform, with AI injecting fault types to train diagnostic capabilities; virtual-real data synchronization is realized via OPC UA protocol to solve differences between physical equipment and virtual models (e.g., robotic arm positioning error <0.5mm).

(3) Engineering comprehensive application stage (25% of total class hours): Enhances engineering innovation and project management capabilities, with steps: Project Introduction → Scheme Implementation → Achievement Transformation. Real enterprise projects are introduced (e.g., intelligent detection unit upgrade and transformation), with AI assisting in requirement analysis and task decomposition. Functional verification is achieved through rapid prototype development and on-site debugging. Performance indicators are optimized (e.g., detection accuracy ±0.02mm) and transformed into teaching cases. A university case shows that the adoption rate of students' project schemes reached 75% in this stage.

3.1.2. Flowchart of the "three-stage nine-step" teaching method

Figure 2 adopts a circular flow design, with the center labeled "Capability Cultivation Objectives" (Equipment Operation → System Debugging → Engineering Innovation). The outer circle is divided into three stages, each containing three steps connected by arrows to form a closed loop: Virtual Simulation Foundation Stage is marked with *Equipment Cognition → Virtual Operation → Virtual-Real Verification*; Production Line Collaborative Training Stage with *Production Line Planning → Virtual Debugging → Virtual-Real Linkage*; Engineering Comprehensive Application Stage with *Project Introduction → Scheme Implementation → Achievement Transformation*. Each step uses icons to distinguish task types (e.g., VR device icon for virtual operation) and labels typical cases and capability achievement indicators (e.g., "First-piece pass rate increased to 85% in the Virtual-Real Verification stage").

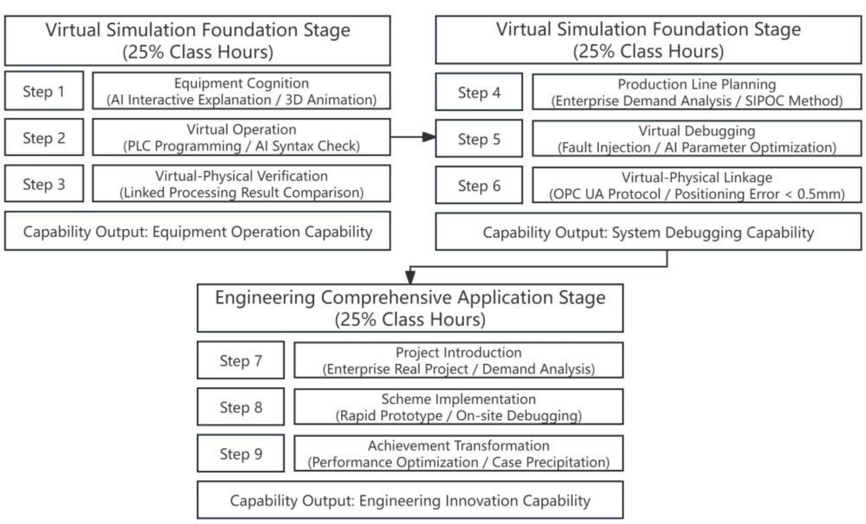

Figure 2. Flowchart of the "three-stage nine-step" teaching method. This teaching method realizes capability leapfrogging from basic operation to engineering innovation through three progressive stages, integrating real enterprise project cases into each stage, which increased students' "1+X" certificate pass rate by 27 percentage points.

3.2. Virtual-real integration construction of digital twin teaching system

3.2.1. Overall architecture of the system

The digital twin teaching system adopts a four-layer architecture: Physical Layer → Data Layer → Model Layer → Application Layer:

(1) Physical Layer: Consists of intelligent manufacturing training equipment (CNC machining centers, industrial robots, etc.), sensor networks (over 200 measurement points for vibration, temperature, etc., with 1kHz sampling frequency), and edge computing gateways, which preprocess data (filtering, feature extraction) and control synchronization accuracy < 1ms.

(2) Data Layer: Builds an industrial data middle platform, integrating real-time databases (InfluxDB for storing equipment operation data), relational databases (MySQL for storing teaching resources), and knowledge graph databases (Neo4j for storing fault cases), supporting 10TB storage capacity and a daily data increment of 400GB.

(3) Model Layer: Constructs multi-scale digital twin models, including geometric models (3D modeling accuracy of 0.01 mm), physical models (material properties, mechanical characteristics), and behavioral models (kinematics, dynamics laws). Computational efficiency is improved through model lightweighting (70% reduction in polygon count via Level of Detail technology) and multi-physics coupling simulation.

(4) Application Layer: Provides four modules—virtual training, intelligent diagnosis, course management, and assessment evaluation—supporting multi-terminal access (PC, tablet, VR devices) with response time < 200ms.

3.2.2. Overview of the digital twin teaching system

The digital twin teaching system adopts a four-layer architecture ("Physical Layer → Data Layer → Model Layer → Application Layer") to realize real-time mapping and deep interaction between physical equipment and virtual models. The Physical Layer deploys over 200 sensors (vibration, temperature, etc.) with 1kHz sampling frequency, preprocesses data via edge computing gateways, and controls synchronization accuracy < 1 ms; the Data Layer builds an industrial data middle platform integrating InfluxDB (10TB storage), MySQL, and Neo4j, supporting daily data increment of 400GB; the Model Layer uses multi-physics coupling modeling technology, achieving high-fidelity reproduction of over 85% industrial scenarios through LOD lightweighting (70% reduction in polygon count) with geometric modeling accuracy of 0.01mm; the Application Layer provides four modules (virtual training, intelligent diagnosis, course management, assessment evaluation) supporting multi-terminal access (PC/tablet/VR) with response time < 200 ms.

Through collaborative operation of the four-layer architecture, the system achieves breakthroughs in key technical indicators: data synchronization delay < 200 ms, virtual-real mapping error < 0.5 mm, and scenario reproduction rate of 85%, providing core technical support for the "Three-Stage Nine-Step" Teaching Method. In teaching applications, real-time data collected by the Physical Layer is processed by the Data Layer to drive dynamic updates of virtual scenes in the Model Layer, allowing students to conduct practical training (equipment operation, fault diagnosis) via the virtual training module in the Application Layer. Practice verification shows that the system increased students' equipment structure cognition accuracy from 68% to 91%, reduced average fault diagnosis time from 112 minutes to 47 minutes, effectively solved pain points of insufficient traditional training resources and high costs, and promoted the transformation of intelligent manufacturing curriculum teaching to a "low-cost, high-fidelity, strong interaction" mode.

4. Exploration of practical paths for intelligent manufacturing curriculum teaching reform

4.1. Construction and application of industrial typical fault case library

4.1.1. Construction standards of the case library and knowledge graph building

The Industrial Typical Fault Case Library covers over 1200 fault scenarios in machinery, electrical systems, and control systems, adopting a three-dimensional classification system of "Equipment Type-Fault Level-Fault Mechanism":

(1) Equipment type: 5 major categories (processing equipment, robotic equipment, etc.) and 20 subcategories;

(2) Fault level: 3 levels (component-level, unit-level, system-level);

(3) Fault mechanism: 4 major categories (mechanical faults like wear/breakage, electrical faults like short circuit/grounding, etc.) and 32 subcategories.

Case data collection follows a standardized template, including fault phenomena (text description, images, videos), cause analysis (fishbone diagram), solutions (maintenance steps, required spare parts), and preventive measures (maintenance cycle, monitoring parameters). A “Fault Phenomenon-Cause-Solution” knowledge graph is built based on case data, containing over 1200 entity nodes and 3500 relational links, supporting semantic reasoning (e.g., inferring “bearing wear” from “motor abnormal noise”).

4.1.2. Industrial typical fault case library

The knowledge graph of the Industrial Typical Fault Case Library constructs a network structure with “fault phenomenon” as the core node, using a four-layer association system of “Fault Phenomenon-Cause-Solution-Associated Equipment”. The core node “Motor Abnormal Noise” radiates via directed edges to nodes like “Cause” (bearing wear, shaft misalignment), “Solution” (replace bearing, re-align), and “Associated Equipment” (CNC machining center, industrial robot). Relationship types (e.g., “causes”, “solves”) are labeled between nodes, and node types are distinguished by color (red for fault phenomena, blue for causes, green for solutions).

The knowledge graph significantly improves fault diagnosis teaching efficiency: average diagnosis time for students reduced from 112 minutes to 47 minutes, with diagnosis accuracy increased to 89%. Its core values include:

(1) Building a standardized fault diagnosis logic chain to help students quickly master the “phenomenon-cause-solution” analysis method;

(2) Realizing associated retrieval of fault cases to support transfer learning across equipment fault mechanisms (e.g., from CNC machining center motor faults to industrial robot motor faults);

(3) Providing knowledge support for intelligent diagnosis systems, automatically generating fault diagnosis reports by matching real-time data with the knowledge graph.

4.2. Construction technology of cloud-based intelligent teaching platform

4.2.1. Overall architecture and resource sharing mechanism of the platform

The cloud-based intelligent teaching platform adopts a Cloud-Edge-Terminal Collaborative Architecture:

(1) Infrastructure Layer: Deploys GPU servers (NVIDIA A100) and storage systems relying on provincial education data centers, realizing elastic scaling via OpenStack to support over 1000 concurrent users.

(2) Platform service layer: Integrates data middle platform (ETL tools, BI analysis), AI service engine (TensorFlow/PyTorch frameworks), and digital twin engine (Unity3D cloud rendering) to provide model training and simulation acceleration services.

(3) Application service layer: Offers microservices like virtual training and intelligent diagnosis (Spring Cloud architecture), supporting PC/VR multi-terminal access.

The resource sharing mechanism uses a “provincial coordination + municipal sub-node” model: CDN acceleration caches popular resources (basic equipment models), reducing access latency for remote areas from 500ms to less than 200ms; collaborative teaching tools support virtual classrooms (video conferences + whiteboard annotation), group collaboration (multi-user synchronous operation of digital twin models), and enterprise mentor remote guidance.

4.2.2. Architecture design of cloud-based intelligent teaching platform

The platform adopts a three-level distributed architecture of “Provincial Central Node-Municipal Sub-node-Terminal Device”, realizing efficient resource sharing and low-latency access via cloud-edge collaboration. Core functions focus on three modules:

(1) Resource management: Unifies storage and dynamic updates of over 1200 industrial fault cases and digital twin models, supporting adaptive loading across terminals;

(2) Collaborative teaching: Breaks time-space constraints with virtual classrooms, group collaboration, and remote enterprise mentor guidance;

(3) Permission Control: Ensures data security and precise resource access based on role-permission models.

Practice verification shows the platform serves 127,000 students, reducing training costs to 17% of physical equipment (83% cost reduction), enabling remote area students to share high-quality virtual training resources, with post capability matching degree increased to 92.7%.

5. Evaluation and verification of teaching reform effects

5.1. Construction and application of the four-dimensional radar evaluation model

5.1.1. Dimension design and index system of the evaluation model

The Four-Dimensional Radar Evaluation Model quantifies teaching reform effects from four dimensions:

(1) Learning satisfaction: Uses a Likert 5-point scale combined with interaction data analysis (course participation, resource access frequency) to measure satisfaction with course content, teaching methods, environment, and teacher guidance.

(2) Capability achievement degree: Evaluates knowledge mastery (theoretical tests), skill proficiency (equipment operation standardization, fault diagnosis accuracy), and engineering literacy (safety awareness, team collaboration), referring to the Intelligent Manufacturing Capability Maturity Model (CMMM) five-level standard.

(3) Industry adaptation degree: Assesses via text similarity analysis of job requirements and course objectives (JD matching degree), post-adaptation period, enterprise satisfaction, and salary level.

(4) Innovation contribution degree: Counts academic innovation (patents, competition awards) and application innovation (technical service projects, economic benefits).

5.1.2. Comparison of the four-dimensional radar evaluation model

Figure 3 uses a radar chart format with four evaluation dimensions on the horizontal axis and standardized scores (0–100) on the vertical axis. Two radar curves are included: solid line for the experimental group (adopting the teaching reform plan) and a dashed line for the control group (traditional teaching). Specific scores are labeled for each dimension:

(1) Learning Satisfaction (Experimental:4.32/Control:3.56);

(2) Capability Achievement Degree (84.6/68.3);

(3) Industry Adaptation Degree (92.7%/75.3%);

(4) Innovation Contribution Degree (78/45).

The experimental group curve is significantly higher than the control group, especially in capability achievement and industry adaptation. The experimental group's comprehensive score is 84.6, an increase of 23.9% over the control group, verifying the effectiveness of the teaching reform plan: post adaptation period shortened from 5.9 months to 2.8 months, with enterprise satisfaction reaching 4.6/5.

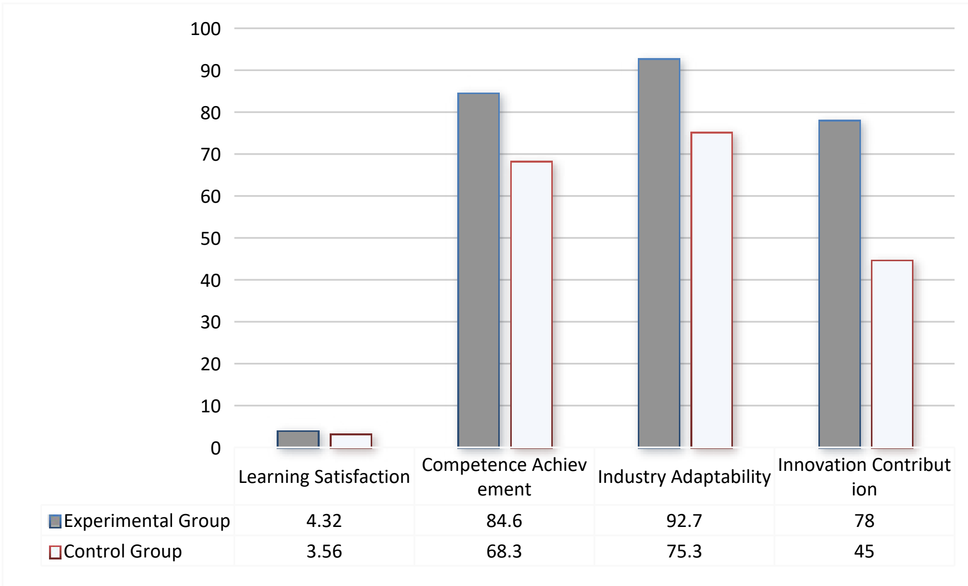

Figure 3. Comparison of the "four-dimensional radar evaluation model."

6. Research conclusions and prospects

6.1. Key research findings

This study constructed a full-chain "Theory-Technology-Practice" solution for generative AI, empowering intelligent manufacturing curriculum teaching reform, with the following key conclusions:

6.1.1. Theoretical mechanism aspect

Proposed the "Dual-Loop Driving" Teaching Model, revealing the collaborative mechanism between the Cognitive Construction Loop and Technology Empowerment Loop, which enriches the theoretical system of educational technology. Established the AI-Enhanced C2D2IO Framework, clarifying the intervention logic of AI in links such as "collaborative(co-creation), virtual debugging, and intelligent operation", expanding the methodology of engineering education.

6.1.2. Teaching model design aspect

Developed the "Three-Stage Nine-Step" Teaching Method and Digital Twin Teaching System, realizing capability progression from basic operation to engineering innovation. The system achieves 85% scenario reproduction rate, <0.5mm virtual-real mapping error, and supports multi-terminal access and high-concurrency processing.

6.1.3. Practice path aspect

Built an industrial typical fault case library with over 1200 cases and a cloud-based platform with the "Provincial Coordination + Municipal Sub-node" model, realizing cross-regional resource sharing. Through the mechanism of integrating enterprise projects into classrooms, 60% of core courses incorporated real projects, and the post-capability matching degree increased to 92.7%.

6.1.4. Effect evaluation aspect

Verification via the "Four-Dimensional Radar Evaluation Model" shows that the teaching reform increased students' capability achievement degree by 23.9%, shortened the post adaptation period to 2.8 months, achieved an enterprise satisfaction score of 4.6/5, and significantly improved innovation contribution (0.32 patents per capita).

6.2. Research limitations and future prospects

6.2.1. Research limitations

Sample representativeness, duration of long-term effect tracking (3 years), and adaptability to technology iteration (updating of digital twin systems).

6.2.2. Future prospects

(1) Expand the sample size to verify the model's universality.

(2) Construct a dynamic adjustment mechanism of "industrial demand-curriculum content".

(3) Deepen research on human-machine collaboration ethics (algorithm bias correction, data privacy protection).

(4) Promote the industrialization of results (development of standardized teaching products).

Disclosure statement

The author declares no conflict of interest.

References

[1] Mo S, Chen KR, Wang Z, et al., 2025, Exploration and Practice of Teaching Reform Paths for Postgraduate Education in Mechanical Engineering. Journal of Mechanical Design, 1: 1–9.

[2] Fu JL, Zhang J, Yang DZ, et al., 2025, Research on Higher Engineering Practice Education System for Intelligent Manufacturing Based on Virtual Simulation. Research and Exploration in Laboratory, 44(10): 180–185.

[3] Zhu CL, Zhou YQ, Wu L, 2024, Curriculum Governance Reform of Vocational Undergraduate Education for Intelligent Manufacturing. Vocational Education Forum, 40(9): 60–67.

[4] Huang X, Hu Y, Dong ZQ, 2025, Theoretical Mechanism, Risk Challenges, and Promotion Paths of Generative Artificial Intelligence Empowering Industrial Transformation and Upgrading. Southwest Finance, (10): 3–15.

[5] Hao N, Gui ZK, 2025, Generative Artificial Intelligence Empowering the Construction of High-Level Research Universities: Scenario Presentation, Risk Generation, and Path Exploration. Journal of Higher Education Management, 20(1): 79–89.

[6] Guo XD, 2025, Practical Dilemmas and Path Optimization of China's AIGC Identification System. Studies in Science of Science, 1: 1–15.

[7] Tian MY, Gu SL, Zhang MH, 2025, Which Feedback from Educational Agents Promotes Learning? A Systematic Literature Review Based on 36 Empirical Studies from 2015 to 2025. Open Education Research, 31(6): 79–92.

[8] Mackenzie D, 2023, Astonishing Progress in Generative Artificial Intelligence Sparks Surprise and Concern. Engineering, 25(6): 9–11.

[9] Zhong BC, Pei YM, 2025, Research on the Impact of Large Model Questioning Strategies and Prompt Frameworks on Learning Outcomes. Open Education Research, 31(6): 93–103.

[10] Cai YW, Chen Z, 2025, A Double-Edged Sword: The Impact of Generative Artificial Intelligence on College Students' Critical Thinking. Journal of Central China Normal University (Humanities and Social Sciences Edition), 64(6): 146–159.

[11] Wang S, 2025, National AI Competence under the Background of "Artificial Intelligence +" Initiative: Strategic Significance, Conceptual Connotation, and Promotion Paths. Popular Science Research, 20(6): 81–90 + 118.

[12] Zhou JL, Liu HM, Wang WH, 2025, From Control to Empowerment: Educational Reflection and Logical Reconstruction of AI-Generated Content Detection Regulations. Journal of Higher Education Management, 20(1): 90–101.

[13] Jiang SY, Hu K, 2025, Attitudes, Strategies, and Enlightenments of World-Class Universities Towards Generative Artificial Intelligence. Heilongjiang Researches on Higher Education, 43(12): 45–54.

[14] Su FL, Zhang LY, 2025, Analysis of Talent Demand in the Generative AI Field Based on Recruitment Information. Library and Information Service, 69(24): 127–138.

[15] Yan JB, 2025, Construction of an Embodied Intelligence-Enabled Experimental Teaching System for Human Factors Engineering. Research and Exploration in Laboratory, 44(12): 158–165.

[16] Chen XS, 2025, Collaborative Thinking with Artificial Intelligence: A New Process of Human Learning. Open Education Research, 31(6): 21–28.

[17] Liu ZM, Chen P, Yu M, et al., 2025, Logic and Paths of Large Models Promoting Educational Knowledge Transformation: From the Perspective of Implementation Science. Open Education Research, 31(6): 68–78.

[18] Zhang KK, 2024, Experiences and Enlightenments of Vocational Education and Training Systems in Germany, the United States, and Japan under the Background of Intelligent Manufacturing. Education and Vocation, (6): 83–89.

[19] Shen T, Xiao YQ, 2023, Interdisciplinary Innovative Education for Intelligent Manufacturing: A New Paradigm Led by Design Thinking. Research in Higher Education of Engineering, (2): 45–50.

[20] Ju LK, Xu JC, Zhou C, 2022, Rational Reflection and System Transformation of Higher Engineering Practice Teaching from the Perspective of Emerging Engineering Education. Jiangsu Higher Education, (12): 128–131.

[21] Zhu CL, Li HT, 2021, Innovation of Talent Training Mode for Undergraduate Vocational Education Towards Intelligent Manufacturing. Vocational Education Forum, 37(8): 21–26.

[22] Zhao HJ, Qi XG, Luo TH, et al., 2020, Research on Emerging Engineering Talent Training for Robot Engineering Major in Local Universities. Journal of Southwest China Normal University (Natural Science Edition), 45(6): 127–132.