Practice of the Artificial Intelligence-Empowered Industry-Education Integration Teaching Model in Mechanical Engineering: Taking Corporate Project-Based Teaching as a Case Study

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Abstract: *The acceleration of technological innovation and industrial upgrading in the field of mechanical engineering has placed profound demands for transformation in the cultivation models of specialized talents. This study, using corporate project-based teaching as a vehicle, explores systematic pathways for artificial intelligence technology to empower the industry-education integration teaching model in mechanical engineering. The research constructs a comprehensive theoretical framework spanning technological integration pathways, teaching model implementation, and effectiveness evaluation: first, it analyzes how artificial intelligence achieves deep integration with specialized instruction through constructing intelligent intermediary layers, restructuring knowledge networks, and establishing dynamic digital twins coupling; second, it elaborates an implementation framework guided by corporate projects, comprising the organization of intelligent resources, the restructuring of human-machine collaborative processes, and cross-scenario data feedback; finally, it proposes effectiveness evaluation methods based on technology integration mapping, analysis of alignment with industrial demands, and an adaptive evaluation system. The study aims to provide theoretical reference and practical guidance for establishing a new paradigm in mechanical engineering education that responds to real-time industrial needs, is driven by data intelligence, and possesses self-evolution capability.*

Keywords: *Artificial Intelligence, Mechanical Engineering, Industry-Education Integration, Teaching Models, Corporate Project-Based Teaching*

Introduction

The core challenge currently facing mechanical engineering education lies in the increasingly prominent lag and gap between the relatively stable disciplinary knowledge system and the rapidly evolving application of industrial technologies. Traditional teaching models reveal limitations in cultivating students' ability to address complex, uncertain real-world engineering problems and to master emerging intelligent tools. Therefore, exploring a teaching model that can organically bridge educational processes with industrial practices and adapt autonomously to technological advancement is of urgent practical necessity. This study focuses on the enabling role of artificial intelligence technology, using authentic corporate projects as the pivot for integrated teaching. Its significance extends beyond the mere application of technological tools, aiming to reconstruct the structure, processes, and evaluation mechanisms of teaching at a systemic level. By deeply integrating the perceptual, decision-making, and interactive capabilities of artificial intelligence throughout the entire teaching chain, this research strives to elucidate how to construct a dynamic, precise, and evolvable educational ecosystem. Such an ecosystem would enable the objectives, processes, and outcomes of talent cultivation to remain synchronized with, or even proactively interact with, the trajectory of industrial technology, thereby providing core theoretical support and feasible architectural design for the paradigm shift in mechanical engineering education.

1. Construction of Integration Pathways for Artificial Intelligence and Mechanical Engineering Teaching

1.1 Embedding Artificial Intelligence Technology in the Context of Mechanical Engineering Teaching

The integration of artificial intelligence technology into the context of mechanical engineering teaching essentially involves introducing data-driven approaches and intelligent algorithms into the traditional structure of knowledge delivery and skill training. This process is not merely a superficial addition of tools; rather, it utilizes core capabilities such as machine learning, computer vision, and natural language processing to reshape the generation, presentation, and interaction methods of teaching content. For instance, in teaching mechanisms or dynamics, physics-informed neural networks can construct high-fidelity virtual simulation environments, replacing certain validation stages that rely on physical equipment, thereby making the dynamic behaviors of complex systems visualizable and analyzable. The key to technological embedding lies in constructing an intelligent intermediary layer compatible with the existing curriculum system and experimental facilities. This layer is responsible for aligning and translating industrial data streams, algorithmic models, and teaching objectives[1].

The effectiveness of this intelligent intermediary layer depends on its precise mapping of domain-specific semantics within mechanical engineering. This requires the artificial intelligence models to not only possess general computational capabilities but also integrate professional domain-specific constraint rules and prior knowledge, such as material mechanical properties, tolerance and fit standards, or typical failure modes. Consequently, the embedding of technology is accompanied by a data-driven reconstruction of teaching resources, transforming traditional drawings, manuals, and case studies into structured, algorithmically accessible knowledge graphs. This deep integration enables the teaching system to evolve from a static knowledge repository into a dynamically responsive system. It can adapt the depth and breadth of teaching content in real-time, based on students' learning behavior data and project task requirements.

1.2 Knowledge Structure Reorganization Mechanism Based on Corporate Project Tasks

The introduction of corporate project tasks creates a deconstructive demand for the inherently discipline-centric knowledge system of mechanical engineering. Knowledge from traditionally linear courses such as "Mechanical Design," "Mechanical Manufacturing Processes," and "Mechanical Control Engineering" manifests in real corporate projects as a highly interdisciplinary, parallel, and problem-oriented integrated state. In this process, the role of artificial intelligence is to construct a dynamic knowledge linking and recommendation engine. This engine can parse the technical requirements within a project task description-such as "lightweight structures," "vibration suppression," or "intelligent assembly"-and automatically link relevant theoretical knowledge points, design methodologies, and analysis tools scattered across multiple courses, thereby forming a temporary knowledge network tailored to the specific project.

This reorganization mechanism transcends modular assembly, driving the transformation of the knowledge structure from a "reserve-based" model to one of "on-demand deployment." The core teaching activity thus shifts to guiding students in performing effective navigation and precise invocation within this dynamic knowledge network. By analyzing solution libraries and iteration logs from past similar projects, the artificial intelligence system can identify critical technical decision points, common pitfalls, and innovative pathways, thereby translating implicit engineering experience into teachable design logic. Consequently, the knowledge structure is no longer a predetermined syllabus but an evolving and growing organism that develops alongside the project's progression. Its reorganization is consistently guided by the ultimate objective of completing a specific engineering artifact with defined functions, performance criteria, and constraints.

1.3 Dynamic Coupling Between Teaching and Production Processes Driven by Artificial Intelligence

Artificial intelligence provides a technological pathway for achieving real-time, dynamic coupling between teaching and production processes. This coupling is established upon the sharing of data and models. The teaching system accesses anonymized real-time production data streams-such as production line sensor data, equipment status logs, or quality inspection images-through controlled interfaces. This grounds the analysis, diagnosis, and optimization activities within classroom teaching in the actual context of the current industrial environment, rather than relying on idealized theoretical models. For instance, by introducing real-time collected vibration signals from computer numerical control (CNC) machine tools into fault diagnosis instruction, students engage with dynamic problems that are synchronized with the production floor. The feasibility of their proposed solutions can then be directly validated against real-world operating conditions.

The advanced form of dynamic coupling manifests as the interaction between the teaching system and the production system at the level of digital twins. The teaching environment can construct digital twins of key production equipment or entire production lines. These twins not only map the status of physical entities in real time but can also predict their future behaviors or conduct hypothetical simulations based on artificial intelligence. Students can safely conduct experiments on these digital twins, such as optimizing process parameters, adjusting layouts, or performing flexible production scheduling. The operational strategies and their impacts can be rapidly evaluated and fed back. This coupling establishes a "secure sandbox" from teaching to production and a "problem source" from production feedback to teaching, forming a bidirectional closed loop. This ensures the continuous iterative updating of both the advancement of teaching content and the engineering relevance of teaching outcomes[2].

2. Implementation Framework of the Intelligent Teaching Model for Industry-Education Integration

2.1 Corporate Project-Oriented Logic for Organizing Intelligent Teaching Resources

The core principle of the corporate project-oriented logic for organizing teaching resources lies in the transformation from static curriculum resource repositories to a dynamic, on-demand aggregated intelligent resource network. This network uses project tasks as its triggering hub. When a specific project requirement is defined, the artificial intelligence system, based on semantic understanding and association rules, actively extracts, assembles, and sequences relevant resource units from dispersed teaching materials, industrial case libraries, standard specification databases, and simulation tool sets. This organizational method no longer adheres to a fixed textbook chapter sequence but instead generates a personalized resource supply chain that closely aligns with the project solution path. The resource units themselves are tagged with rich metadata describing their corresponding knowledge type, skill level, application scenario, and strength of association with other resources, thereby enabling precise matching.

The operational efficacy of this dynamic resource network relies on a continuously evolving resource mapping model. By recording and analyzing the frequency of students' calls to different resource units, their dwell time, and the subsequent application outcomes during the project progression, the model continually optimizes the matching relationships between resources and tasks, as well as between resources and learners. Consequently, the teaching resources become adaptive, capable of providing differentiated content combinations and presentation formats in response to the selection of different technical pathways within similar projects or the varying cognitive foundations of different student groups. The logic of resource organization thus shifts from being supply-driven to being demand-pulled. Its ultimate goal is to construct a multi-dimensional resource environment that is isomorphic with the real-world engineering problem-solving process and supports flexible exploration.

2.2 Teaching Reconstruction of Design and Manufacturing Processes Through Human-Machine Collaboration

The reconstruction of design and manufacturing process teaching through human-machine collaboration manifests in transforming the traditional linear and sequential teaching stages of "design-analysis-process-manufacturing" into a concurrent collaborative network centered on intelligent agents. Within this network, artificial intelligence agents undertake tasks such as rule-based computation, rapid iteration of multiple solutions, early warning of potential conflicts, and data integration. For instance, during the conceptual design phase, generative design algorithms can automatically provide multiple topology optimization schemes based on set constraints. In the design review stage, rule-based intelligent agents can instantly detect missing dimensional annotations or manufacturability defects in drawings. The role of students shifts to focus more on requirements definition, constraint trade-offs, creative proposal, and the evaluation and decision-making regarding intelligently generated outcomes-that is, on addressing higher-level problems of engineering synthesis and value judgment[3].

This reconstruction establishes a teaching process threaded by a "digital thread." From the initial design intent to the final product feedback, all data, decisions, and changes are recorded, linked, and traced within a unified digital thread. Artificial intelligence ensures the continuity and consistency of this thread, enabling students to clearly discern the impact of their upstream decisions and the constraints of downstream processes at any point in the teaching workflow. The focus of process teaching thus shifts from instructing isolated software operations or procedural steps to training students on how to effectively plan task flows, manage the transfer and transformation of design intent within an environment of clear human-machine division of labor, and utilize the output of intelligent tools to deepen their understanding of complex engineering systems.

2.3 Integration of Cross-Scenario Learning Data Flows and Design of the Feedback System

The integration of cross-scenario learning data flows aims to dismantle the data barriers between the classroom, virtual simulation environments, experimental platforms, and corporate project sites. This integration is achieved by constructing a unified data access layer and standardized data models, which transform students' operational behaviors, interaction logs, process data, work products, and environmental status information from different scenarios into structured data streams with consistent semantics. These multi-source, heterogeneous data are then aggregated into a central data lake or data middle platform, providing the raw material for subsequent analysis and feedback. The key to data integration lies in defining a mapping system for cross-scenario learning behaviors and competency indicators, ensuring that signals from diverse sources can be correlatively interpreted.

Based on the integrated full-process data, the design of the feedback system transcends traditional scoring evaluation, shifting towards deep profiling and intervention in the formation of engineering competencies. Artificial intelligence models, such as time-series analysis models and clustering algorithms, are employed to identify students' learning patterns, skill acquisition trajectories, decision-making preferences in complex tasks, and potential cognitive bottlenecks. The system can generate fine-grained diagnostic feedback that not only points out errors but also reveals the underlying thought processes or knowledge structure deficiencies. Feedback is delivered in a contextualized manner-for example, providing a review of relevant theory simultaneously when a design simulation fails, or prompting key machining considerations when encountering specific materials during process planning. This system establishes a closed loop from multi-source data collection to the provision of personalized cognitive scaffolding, driving the evolution of the teaching model from experience-based guidance to data-intelligence-driven instruction.

3. Evaluation Dimensions and Methods for the Teaching Efficacy Empowered by Artificial Intelligence

3.1 Mapping Relationship Between Technology Integration Degree and Professional Competency Development

Evaluating the teaching efficacy empowered by artificial intelligence requires, as a primary task, deconstructing the nonlinear mapping relationship between the degree of technology integration and the development of mechanical engineering professional competencies. The degree of technology integration does not refer simply to the frequency of using technological tools, but is characterized through multidimensional indicators. These include the decision-making weight of algorithmic models in solving specific engineering problems, the coupling depth between intelligent systems and traditional workflows, and the circulation efficiency of multi-source data within the teaching closed loop. Correspondingly, the assessment of professional competency development must transcend traditional knowledge testing to encompass higher-order dimensions such as systems thinking, complex problem modeling, decision-making under uncertainty, and human-machine collaborative innovation. Establishing a mapping between the two necessitates constructing a dynamic correlation model capable of identifying the activation states and development rates of various competency elements under different levels of integration[4].

The empirical basis for this mapping relationship stems from the analysis of full-process data collected from the learning journey. By gathering students' procedural data generated during interactions with intelligent systems-such as the frequency of adopting and modifying algorithmic suggestions, the breadth of exploring parameter optimization paths during virtual debugging, and the evaluation logic demonstrated when assessing multiple intelligently generated solutions-it becomes possible to quantitatively analyze how specific technology integration patterns shape cognitive structures and problem-solving strategies. The value of the mapping model lies in its diagnostic and predictive capabilities. It can reveal the optimal technology integration scenarios and resource configurations required to achieve specific competency goals, such as "innovative design capability under multiple constraints," thereby providing a basis for the precise optimization of the teaching model.

3.2 Analysis of the Alignment Between Project Teaching Outputs and Industry Technical Requirements

Another core dimension for evaluating teaching efficacy lies in the alignment between the outputs of teaching activities and current as well as near-future industry technical demands. This alignment analysis must move beyond static checklist comparisons of skills, focusing instead on attributes such as the innovativeness, engineering complexity, and solution robustness inherent in the outputs. The analytical framework is constructed upon a deconstruction of the industry's technical landscape. Utilizing natural language processing and knowledge graph technologies, it continuously parses the research and development directions, patent portfolios, recruitment demands, and technical white papers of leading enterprises to extract key clusters of technical capabilities, trends in toolchain evolution, and typical engineering challenges. The outputs of project-based teaching—including design documents, simulation reports, prototype performance data, and solution logic—are then positioned and compared within this dynamic landscape.

The key to alignment analysis lies in establishing a set of computable metrics for semantic similarity and complexity measurement. By performing embedding calculations between the structured descriptions of project outputs and the industry's technical requirement knowledge graph, the strength of their association with specific technological domains-such as additive manufacturing process optimization or digital twins for mechatronic systems-can be quantified. Concurrently, by analyzing the number of variables handled in the design scheme, the dimensionality of considered constraints, and the innovation level of the methods employed, its benchmarking level for engineering complexity can be assessed. This analysis not only evaluates the degree of alignment but also identifies the position and potential value of teaching outputs within the industry's technology chain, revealing both the degree of fit and the leading potential between talent cultivation standards and the evolution of industrial technology[5].

3.3 Construction of an Intelligent Evaluation System for the Sustainable Evolution of the Teaching Model

Establishing an intelligent evaluation system with sustainable evolutionary capability is fundamental to ensuring that the teaching model can dynamically adapt to technological advancements and industrial changes. The core characteristic of this system lies in its endogenous learning mechanism. Its evaluation models are not static; instead, they are capable of undergoing periodic or triggered self-updates and parameter adjustments based on the continuous influx of multi-source evaluation data. This data includes the aforementioned integration mapping data, industry alignment data, student learning outcome data, and the teaching system's own operational logs. By utilizing meta-learning or online learning algorithms, the system continuously identifies new factors influencing efficacy and refines evaluation dimensions, optimizing the weighting relationships among different evaluation indicators. Consequently, the evaluation criteria themselves co-evolve in tandem with the external environment[6].

This intelligent evaluation system features an architecture of multi-layered feedback loops. The inner loop focuses on the immediate adjustment of specific teaching activities, providing formative assessment feedback based on the analysis of students' micro-level behaviors and process outputs. The outer loop, in contrast, addresses the iteration of the macro-level model. It synthesizes aggregated data across cycles and projects to evaluate the overall effectiveness and adaptability of the teaching model's framework, generating strategic optimization recommendations such as "introducing certain emerging algorithmic tools to address new industrial design paradigms" or "adjusting the human-machine task allocation ratio in specific teaching phases." Through this multi-layered, closed-loop, and self-adaptive evaluation process, the teaching model is transformed from a static design blueprint into an intelligent organism capable of continuous sensing, diagnosis, learning, and evolution.

Conclusion

This study systematically constructs a theoretical framework for the artificial intelligence-empowered industry-education integration teaching model in mechanical engineering, clarifying its progressive logic from technological pathway integration and teaching framework implementation to intelligent efficacy evaluation. The research indicates that the core of this model lies in leveraging the deep involvement of artificial intelligence to construct a new type of teaching organism, dynamically driven by corporate projects, powered by data intelligence as its neural network, and fueled by real-time bidirectional industry-education feedback as its circulatory force. It not only reconstructs the method of knowledge transmission from static predetermination to dynamic on-demand deployment but also facilitates the transformation of teaching processes from linear sequences to human-machine collaborative networks. Ultimately, it renders the evaluation of teaching effectiveness and the optimization of the model itself an intelligent process endowed with endogenous growth potential. Future research and practical directions may focus on the following aspects: first, exploring more fine-grained models of human-machine cognitive division of labor and collaboration to further unleash teaching innovation potential; second, developing more universal and domain-adaptive intelligent teaching middleware and data standards to lower implementation barriers; third, deepening the modeling of long-cycle learning trajectories and emergent competency patterns to support more precise predictive and guided interventions by the teaching system, thereby continuously advancing the intelligent evolution of the mechanical engineering education ecosystem.

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