

# Title: Research on Innovation of Industry-Education Integration Apprenticeship Training Model in Engineering Design Industry Empowered by Artificial Intelligence

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**Abstract:** The rapid onset of the Fourth Industrial Revolution has fundamentally disrupted the operational paradigms of the engineering design industry, transitioning from traditional labor-intensive drafting to data-driven, generative, and intelligent design methodologies. However, the prevailing talent cultivation mechanisms — specifically the "Industry-Education Integration" (IEI) and the modern apprenticeship system—exhibit a significant hysteresis, failing to align the pedagogical supply with the evolving industrial demand. This structural misalignment manifests as a decoupling of academic curriculum from complex engineering practice and an inherent inefficiency in the transmission of tacit knowledge within the traditional master-apprentice relationship. This study rigorously explores the innovative application of Artificial Intelligence (AI) to restructure the apprenticeship training model. By synthesizing theories of Situated Learning, Cognitive Apprenticeship, and the SECI Knowledge Management model, this paper proposes an "AI-Empowered Dual-Tutor" framework. This architecture integrates Domain-Specific Knowledge Graphs for dynamic curriculum reconstruction, Generative AI Agents for personalized cognitive scaffolding, and Digital Twin technologies for immersive, risk-free simulation. The research argues that AI does not supplant the human mentor but rather "externalizes" the mentor's implicit knowledge, thereby accelerating the novice-to-expert transition, resolving the scarcity of high-level mentorship resources, and fostering a sustainable ecosystem for high-quality engineering talent cultivation.

**Keywords:** Artificial Intelligence; Engineering Design; Industry-Education Integration; Modern Apprenticeship; Tacit Knowledge; Educational Innovation; Digital Twins.

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## Introduction

The engineering design sector serves as the intellectual vanguard of the construction and manufacturing industries, determining the technical feasibility, economic viability, and aesthetic value of national infrastructure. Historically, the cultivation of competence in this field has relied heavily on the "Master-Apprentice" system, a pedagogical lineage rooted in medieval guilds where knowledge transmission was strictly interpersonal, observational, and time-intensive. In this traditional paradigm, the "master" served as the sole repository of technical expertise and professional ethics, transmitting wisdom through years of close supervision. However, the contemporary engineering landscape is characterized by an explosion of complexity—multidisciplinary collaboration, stringent regulatory compliance, and the integration of sustainable technologies—which has rendered the traditional, linear transmission of knowledge increasingly inefficient. The scarcity of experienced senior engineers, coupled with the pressure of project delivery timelines, has eroded the quality of mentorship, leaving apprentices often relegated to repetitive drafting tasks without gaining insight into high-level design logic.

Simultaneously, the national strategic imperative of "Industry-Education Integration" (IEI) seeks to bridge the chasm between the theoretical abstraction of higher education and the practical exigencies of the corporate world<sup>[1]</sup>. Despite policy support, the implementation of IEI in engineering design often remains superficial, characterized by sporadic internships and disconnected curriculum designs. Universities often lack access to the latest industrial data and workflows, while enterprises lack the pedagogical expertise to convert their production experience into structured learning content. This dichotomy results in a "skills gap" where graduates possess theoretical knowledge of mechanics and mathematics but lack the "engineering intuition"—the tacit knowledge required to solve ill-defined, real-world problems.

The emergence of Artificial Intelligence (AI), particularly the breakthroughs in Large Language Models (LLMs), Generative Adversarial Networks (GANs), and Knowledge Graph technologies, offers a disruptive opportunity to resolve these systemic contradictions. AI possesses the unique capability to process vast amounts of heterogeneous engineering data, simulate complex design scenarios, and provide adaptive, personalized feedback at scale<sup>[2]</sup>. This paper posits that integrating AI into the apprenticeship model is not merely a technological upgrade but a fundamental epistemological shift. It aims to answer the critical research question: How can AI technologies be systematically embedded into the IEI apprenticeship model to externalize tacit knowledge, optimize mentorship resource allocation, and enhance the efficiency of engineering talent cultivation? Through a theoretical analysis and model construction, this study charts a pathway for an AI-empowered educational paradigm.

## 1 Theoretical Framework and Literature Review

### 1.1 Cognitive Apprenticeship and Situated Learning

The theoretical foundation of engineering education is deeply rooted in the concept of "Situated Learning" proposed by Lave and Wenger, which argues that learning is a function of activity, context, and culture. They introduced the concept of "Legitimate Peripheral Participation" (LPP), suggesting that novices learn by gradually moving from the periphery of a community of practice to its center. Collins and Brown further refined this into the "Cognitive Apprenticeship" model, which emphasizes the necessity of making thinking visible. In engineering, this means articulating the internal cognitive processes—how a chief engineer identifies a problem, decomposes it, and selects a solution. However, current literature indicates that in modern, high-pressure design institutes, mentors often fail to articulate these cognitive processes due to time constraints, leaving apprentices to rely on inefficient trial-and-error learning. The challenge lies in creating a "cognitive scaffold" that supports the learner when the human mentor is unavailable.

## 1.2 The SECI Model and Tacit Knowledge Management

Engineering design is a knowledge-intensive activity that relies heavily on "Tacit Knowledge"—the kind of knowledge that is difficult to transfer to another person by means of writing it down or verbalizing it (e.g., design intuition, aesthetic judgment). Nonaka and Takeuchi's SECI model (Socialization, Externalization, Combination, Internalization) provides a powerful lens for analyzing this transfer. Traditional apprenticeship relies almost exclusively on Socialization (face-to-face observation). The critical bottleneck in current IEI models is Externalization—converting the mentor's gut feeling into explicit rules or case studies that can be shared. Recent scholarship in Knowledge Management suggests that AI technologies, through pattern recognition and natural language processing, can serve as a potent tool for Externalization, capturing the unstructured data of expert workflows and converting them into explicit learning assets.

## 1.3 AI in Education (AIEd): From CAI to Intelligent Adaptive Systems

The application of AI in education has evolved from simple Computer-Aided Instruction (CAI) to complex Intelligent Tutoring Systems (ITS). In the specific domain of engineering, AI plays a dual role: it is both a tool for design (e.g., Generative Design in BIM software) and a tool for learning. Current research highlights the potential of AI to personalize learning paths. Unlike a standardized university syllabus, an AI system can analyze a student's performance data to identify specific weaknesses—for instance, a deficiency in seismic load calculation—and dynamically generate remedial exercises. This capability addresses the heterogeneity of apprentices' backgrounds. However, most existing studies focus on AI in classroom settings; there is a paucity of research on how AI can be integrated into the dynamic, project-based environment of a corporate apprenticeship, which is the focus of this study.

## 2 Diagnosis of Deficiencies in the Traditional IEI Apprenticeship Model

To construct a robust innovative model, it is imperative to first rigorously diagnose the structural pathologies of the existing apprenticeship system within the engineering design industry. The current model is plagued by three primary dimensions of inefficiency that hinder effective talent cultivation.

First, there is a severe asymmetry in the supply and demand of high-quality mentorship resources. In typical engineering design firms, senior engineers (mentors) are the core production assets, often overseeing dozens of simultaneous projects. Their primary KPI is project delivery and risk control, not pedagogy. Consequently, the "Master-Apprentice" relationship often devolves into a managerial relationship where the apprentice is used as low-cost labor for repetitive drafting tasks ("drawing hands"). The mentor lacks the temporal bandwidth to provide deep, reflective guidance or to explain the "why" behind design decisions. This leads to a "sheep-herding" effect where one mentor is nominally assigned to multiple apprentices but provides minimal actual instruction, resulting in a prolonged and flattened learning curve for the novices.

Second, the system suffers from the "Black Box" phenomenon of tacit knowledge transmission. Engineering expertise is often non-codified; it exists in the form of intuition developed over decades. A senior structural engineer might intuitively know that a certain column layout is unstable without needing to run a calculation, based on pattern recognition from previous failures. In the traditional model, an apprentice can only acquire this knowledge through years of observation, hoping to encounter similar situations. There is no systematic mechanism to extract, store, and retrieve this experiential wisdom. When a senior engineer retires or leaves the firm, their tacit knowledge creates a "knowledge void," forcing the organization and the apprentices to relearn lessons from scratch. The transmission is inefficient, sporadic, and highly dependent on the specific projects the firm happens to be working on at the time.

Third, there is a fragmentation between academic theoretical knowledge and industrial technological iteration. The pace of technological change in the engineering industry—exemplified by the adoption of Building Information Modeling (BIM), Parametric Design, and Green Building simulations—far outstrips the speed of curriculum reform in universities. The "Industry-Education Integration" often fails because the knowledge apprentices bring from the university is obsolete upon arrival. Furthermore, the apprenticeship process is often unsystematic; it is dictated by the randomness of project assignment. If an apprentice is assigned to a team specializing in residential high-rises, they may complete their apprenticeship without ever encountering the unique challenges of steel-structure commercial buildings or underground infrastructure, leading to a "siloed" competency profile that lacks interdisciplinary adaptability.

## 3 Construction of the AI-Empowered Dual-Tutor Apprenticeship Model

Addressing the aforementioned structural deficiencies, this study proposes an innovative "AI-Empowered Dual-Tutor" model. This model fundamentally re-engineers the apprenticeship ecosystem by integrating Human Intelligence (HI) with Artificial Intelligence (AI) to create a seamless, ubiquitous, and adaptive learning environment. The architecture consists of four synergistic layers.

### 3.1 The Data Infrastructure Layer: The Domain-Specific Knowledge Graph

The foundation of this model is data. Engineering design firms possess massive archives of historical data, including CAD drawings, BIM models, calculation sheets, review comments, and project correspondence. However, this data is mostly unstructured and "dark." We propose utilizing Optical Character Recognition (OCR), Natural Language Processing (NLP), and Semantic Analysis to mine this repository and construct a "Dynamic Engineering Knowledge Graph." This graph links abstract theoretical concepts (e.g., "shear capacity") with specific regulatory codes, historical project cases, common error patterns, and expert reasoning paths. Unlike a static textbook, this Knowledge Graph is a living entity that evolves with every new project. It serves as the "externalized brain" of the collective enterprise, ensuring that the tacit knowledge of senior engineers is captured and codified, making it retrievable for apprentices at the point of need.

### 3.2 The Interactive Layer: The Intelligent Virtual Mentor

The core innovation is the introduction of an AI Agent acting as a "Virtual Mentor" to complement the human master. Built upon Large Language Models fine-tuned on the engineering corpus, this Virtual Mentor provides 24/7 scaffolding. It functions on three levels:

**Contextual Q&A:** When an apprentice encounters a hurdle in a design software (e.g., Revit) or a code interpretation issue, the AI provides instant, context-aware answers, citing specific national standards and internal company best practices.

**Socratic Prompting:** Instead of merely providing solutions, the AI is programmed to ask guiding questions to stimulate critical thinking (e.g., "You selected a C30 concrete grade, but considering the 40-story height and seismic zone, have you evaluated the implications for column size?").

**Generative Exploration:** In the conceptual phase, the AI can generate multiple design variants based on the apprentice's constraints, allowing the novice to explore a solution space far wider than their limited experience would normally permit, thus accelerating the development of "design intuition."

### 3.3 The Scenario Layer: Digital Twins and Immersive Simulation

Engineering design carries high risks; a mistake in the real world can be catastrophic. Therefore, traditional apprenticeships limit novices to low-risk, peripheral tasks. The AI model introduces "Digital Twin" technology to create high-fidelity virtual simulations of construction projects. Within this immersive environment (accessed via VR/AR or desktop), apprentices can engage in "Virtual Construction." They can test design hypotheses—for instance, changing the HVAC duct layout—and the AI-driven physics engine will immediately simulate the consequences, such as clashes with structural beams or insufficient maintenance headroom. This allows for "failure-based learning" in a safe environment. The AI tracks the apprentice's behavioral patterns within the simulation, identifying cognitive gaps (e.g., consistently ignoring fire safety spacing) and reporting these to the human mentor for targeted intervention.

### 3.4 The Collaborative Layer: Human-AI Synergy and Role Transformation

The introduction of the Virtual Mentor does not render the human mentor obsolete; rather, it elevates their role. The "Dual-Tutor" system operates on a division of labor<sup>[3]</sup>: the AI handles the transmission of Explicit Knowledge (codes, software operation, standard calculations, routine checks), which constitutes 70% of the training burden. This liberates the human mentor to focus on Tacit and Strategic Knowledge (professional ethics, client negotiation, complex trade-off decision-making, creative leadership, and career planning). The relationship shifts from a hierarchical "instructional" model to a collaborative "co-creation" model. The human mentor uses the analytics dashboard provided by the AI to monitor the apprentice's progress and intervenes only when high-level guidance is required, significantly improving the efficiency of mentorship resource utilization.

## 4 Implementation Pathway and Policy Recommendations

The transition from a traditional apprenticeship to an AI-empowered model is a complex systemic engineering task that requires coordinated efforts across curriculum design, technological deployment, and organizational management.

### 4.1 Co-Construction of the Digital Curriculum Resource Pool.

Universities and partner enterprises must collaborate to digitize industrial knowledge. This involves "data cleaning" of historical enterprise projects to create the training set for the Knowledge Graph. Curricula must be redesigned to move away from rote memorization. Instead of teaching "How to calculate a beam" (which AI can do), the curriculum should focus on "How to evaluate if the AI's calculation is correct" and "How to prompt the AI for optimal design." This establishes the foundational "AI Literacy" required for the new model.

### 4.2 Development of the Intelligent Evaluation Platform.

Traditional assessment is subjective and result-oriented. The new model requires a process-oriented evaluation system. An Intelligent Evaluation Platform should be developed that collects multimodal data: logs of the apprentice's interaction with the AI, the speed of design iteration, error rates in simulation, and even eye-tracking data to assess focus. This data feeds into a "Competency Radar Chart" for each apprentice, allowing for precision teaching. For example, if the system detects that an apprentice excels in mechanics but struggles with spatial coordination, it will automatically push more 3D spatial reasoning modules to their learning path.

### 4.3 Institutional Reform and Incentive Mechanisms.

To ensure sustainability, the "Dual-Tutor" system needs policy validation. Academic institutions should recognize the AI-assisted training hours as legitimate credit. Enterprises must establish incentive mechanisms for human mentors, rewarding them not just for project output but for their contribution to "training the AI" (e.g., annotating data, verifying AI outputs). Furthermore, intellectual property (IP) protocols must be established. Since the AI learns from proprietary company data, clear legal frameworks must be defined regarding data ownership and

security to encourage enterprises to open their "black box" of data for educational purposes.

## 5 Discussion: Implications, Challenges, and Ethics

The proposed AI-empowered model represents a paradigm shift from "Experience-Driven" to "Data-Intelligence-Driven" vocational education. By externalizing tacit knowledge and providing ubiquitous scaffolding, this model democratizes access to high-quality mentorship, potentially leveling the playing field for students from less prestigious institutions who may not have access to top-tier human masters. It aligns the speed of learning with the speed of technological iteration, ensuring that the engineering workforce remains agile and competitive.

However, significant challenges and ethical risks warrant rigorous discussion. First is the risk of "Algorithmic Dependency" and De-skilling. If apprentices rely too heavily on AI to generate designs and check codes, they may fail to internalize the fundamental "First Principles" of engineering. In a crisis where AI tools are unavailable or hallucinate, such engineers would be incompetent. Therefore, the pedagogical design must emphasize "Verification and Validation" as a core competency, requiring apprentices to manually verify AI outputs periodically.

Second is the "Black Box" nature of AI decision-making. In engineering, explainability is crucial for liability. If an AI suggests a design parameter, the engineer must understand the why. Current Deep Learning models often lack this transparency. Future development must focus on Explainable AI (XAI) to ensure that the educational tool provides reasoning, not just answers.

Third is the shift in Professional Identity. As AI takes over technical rationality, the value of the human engineer shifts towards creativity, empathy, and ethical judgment. The apprenticeship model must therefore increase the weight of humanities, ethics, and social sciences in engineering education, cultivating "Grand Engineers" who can navigate the socio-technical complexities of the future built environment.

## 6 Conclusion

This research has systematically explored the integration of Artificial Intelligence into the Industry-Education Integration apprenticeship model within the engineering design industry. By identifying the limitations of the traditional model—specifically the bottleneck of tacit knowledge transmission and the scarcity of mentorship resources—we have proposed an "AI-Empowered Dual-Tutor" framework. This framework leverages Knowledge Graphs, Virtual Mentors, and Digital Twin simulations to create a personalized, data-driven, and immersive learning ecosystem.

The conclusion of this study is that AI is not merely a tool for efficiency but a catalyst for pedagogical transformation. It allows for the decoupling of knowledge transmission from the physical presence of the mentor, thereby solving the scale and quality dilemma of traditional apprenticeships. The future of engineering education lies in the "Human-AI Synergy," where the AI assumes the role of the tireless technical tutor, and the human master ascends to the role of a wisdom guide. Implementation of this model requires a concerted effort to digitize industrial assets, reform curricula towards AI literacy, and establish robust ethical guardrails. Ultimately, this innovation will cultivate a new generation of engineering talent that is not only technically proficient but also adept at collaborating with machine intelligence to solve the complex infrastructure challenges of the 21st century.

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