

AI-Empowered Talent Cultivation for Smart Manufacturing: Reconstructing Emerging Engineering Curricula and Innovating Multimodal Pedagogies

Jie Su, Bo Hu*, Hongbing Wang, Lairong Yin, Zeliang Xiao

College of Mechanical and Vehicle Engineering, Changsha University of Science and Technology, Changsha, 410114, China

*Corresponding author: Bo Hu, hubo4956@csust.edu.cn

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Abstract: Amidst the deepening implementation of the Made in China 2025 strategy and the next-generation artificial intelligence revolution, this research addresses critical imperatives for digital transformation in mechanical engineering education. Centered on an AI-driven curricular reconstruction framework, we establish a tripartite reform paradigm integrating knowledge deconstruction, scenario reconstruction, and capability regeneration. Systematic innovations—including intelligent content iteration, cyber-physical teaching spaces, and data-driven assessment transformation—cultivate emerging engineering leaders equipped with systemic cognition of intelligent equipment, proficiency in industrial algorithm development, and cross-disciplinary innovation competencies. The approach constructs deeply coupled ecosystems bridging curricula, industrial demands, and research frontiers, delivering replicable, scalable, and certifiable AI-empowered solutions for core smart manufacturing programs within mechanical engineering disciplines.

Keywords: Smart Manufacturing; Talent Cultivation; Mechanical Engineering; AI Empowerment; Multimodal Pedagogy; Industry-Academia Integration.

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1. Introduction

1.1 Upgraded Demands for Smart Manufacturing Talent Development

Global engineering education is rapidly evolving toward intelligentization, transboundary integration, and ecosystem development. MIT's "New Engineering Education Transformation" initiative embeds machine learning and digital twin technologies into mechanical engineering curricula, with its "Smart Manufacturing Digital Twin Teaching Platform" utilized for Boeing aircraft assembly line simulations^[1]. Germany's "Industry 4.0 Education Plan" integrates industrial IoT and smart factory operations into vocational training via Dual System 2.0, enabling real-time student manipulation of Siemens' Amberg plant production lines. The EU's "EIT Manufacturing" project unites 23 countries to develop interdisciplinary "AI + Mechanical Engineering" curricula emphasizing problem-oriented and data-driven pedagogy. These practices signify a global shift from competency-based training toward intelligence-empowered literacy, prioritizing core capabilities in applying AI toolchains within complex industrial scenarios^[2].

1.2 Profound Impacts of AI Revolution on Mechanical Engineering Education

Technological paradigm shifts are fundamentally restructuring the ontological foundations of engineering education,

catalyzing triple transformations in mechanical engineering knowledge production models: (i) integration of intelligent algorithm clusters (e.g., DNNs, reinforcement learning) with traditional mechanical system modeling, enabling autonomous decision-making in equipment design; (ii) real-time dataflow reconstruction of equipment lifecycle management through industrial IoT architectures, advancing predictive maintenance beyond empirical limitations; (iii) synergistic evolution of multimodal sensing and digital twins, achieving dynamic isomorphism between physical entities and information models in cyber-physical spaces. This technological matrix demands mastery of composite competencies—topology optimization algorithm development, edge computing deployment, and human-machine collaborative decision-making—effectively deconstructing traditional cognitive boundaries in mechanical design. Accelerating the transformation of conventional mechanical programs into emerging engineering disciplines is therefore critical to address paradigm shifts in product intelligentization (new capabilities), AI convergence (new technologies), and multidisciplinary integration (new features).

1.3 Emerging Engineering Education Framework and Core Demands for Smart Manufacturing Talent

China's Emerging Engineering Education initiative, guided by MOE's "Six Excellences & One Peak" Plan 2.0, has spurred innovations including Zhejiang University's "Intelligent Equipment & Robotics" micro-program featuring a tri-level curriculum (mechanical design–deep learning–industrial cloud platforms) and Huazhong University of Science & Technology's collaboration with Huawei on "Intelligent Base Industry-Education Integration Centers" embedding Ascend AI chip development^[3]. Nevertheless, three critical bottlenecks persist: (i) insufficient AI integration—only 12% of mechanical programs mandate industrial big data analytics courses; (ii) fragmented pedagogical scenarios—disconnected virtual simulations and real production data impede holistic competency development; (iii) superficial industry-academia collaboration—limited corporate participation beyond equipment donation hinders deep co-development of technologies and curricula. Comparative analyses reveal that Chinese mechanical graduates exhibit <30% proficiency in intelligent system integration versus international peers. Industry feedback highlights acute misalignments between traditional training and emerging job requirements (e.g., smart line optimization, predictive maintenance), with graduates demonstrating deficiencies in algorithm development, cross-disciplinary thinking, and engineering ethics. Alarming, merely 15% of industrial technicians independently optimize ROS-based robotic path planning algorithms, underscoring severe education-industry gaps^[4].

1.4 Research Objectives, Framework, and Contributions

To address these challenges, we propose an AI-enabled four-dimensional restructuring framework: (i) A dynamic knowledge graph-based curriculum system integrating SolidWorks, ROS, and PyTorch toolchains enables modular nesting of mechanical principles and AI algorithms; (ii) An HPC-powered "cloud-edge-device" experimental system grants remote access to enterprise digital twins with real-time production data; (iii) A multimodal learning analytics platform synthesizing code, operation, and defense data, employing LSTM networks to generate capability growth warning maps; (iv) Co-established "Smart Manufacturing Innovation Workshops" requiring graduation projects on intelligent production line optimization, yielding 37 commercially implemented student innovations within two years.

2. Bottleneck in new engineering disciplines for intelligent manufacturing

2.1 The Chasm Between Traditional Curricula and Frontier AI Technologies

Existing engineering education systems face systemic challenges from emerging intelligent technologies, fundamentally rooted in conflicts between traditional disciplinary paradigms and contemporary innovation frameworks. Rigid disciplinary barriers isolate course content, rendering knowledge architectures inadequate for addressing cross-domain problem-solving demands in fields like smart manufacturing. Analysis of intelligent data technology spectrums reveals scopes exceeding single-discipline capacities—heterogeneous data acquisition, high-dimensional preprocessing, distributed architectures, multi-database systems, hybrid batch-stream processing engines, and multimodal decision-making deeply integrate computer science, mechatronics, biomechanics, and cognitive science. This knowledge-structure imbalance severely constrains cognition and praxis within new engineering paradigms.

Amid global manufacturing intelligence transformation and national strategic imperatives, higher engineering education must cultivate core smart manufacturing talent. This demands establishing a practice-oriented paradigm centered on macro-engineering perspectives, achieved through deep decoupling and reconstruction of knowledge modules to fuse scientific principles, engineering technologies, humanistic intelligence, and social ethics. Crucially, developing students' dynamic adaptability, innovation origination, and systemic integration capabilities in complex production scenarios requires pedagogical systems that track technological evolution. Forward-looking curricula must reshape engineering philosophies and craftsmanship literacy while integrating professionalism and ethical cultivation within advanced training. Such integrated education systems will drive talent supply for smart manufacturing, supporting national innovation strategies.

2.2 Preliminary Explorations in Emerging Engineering Talent Cultivation

The institutionalization of smart manufacturing programs is deconstructing traditional engineering education through its leadership-driven, interdisciplinary, innovative, cross-boundary, and dynamic attributes, compelling comprehensive reconstruction of educational philosophies, training models, goal positioning, curricular ecosystems, practice environments, and pedagogies ^[5]. Practice-based learning—as the topological nexus for capability development—encompasses course experiments, project-based designs, multi-level training cycles (cognition-production-graduation), and innovation platforms, collectively forming cognitively progressive frameworks. However, persistent deficiencies remain:

Educational philosophies exhibit tripartite disproportion: overemphasis on disciplinary foundations and theoretical transmission, undervaluation of competency mapping and contextual practice, and preferential quantitative evaluation over ethical cultivation, impeding macro-engineering thinking for complex problem-solving. Talent cultivation systems lack coherent innovation pathways and elite-incubation mechanisms. Meanwhile, critical shortages exist in dual-qualified instructors, training facilities, and cutting-edge equipment, compounded by insufficient knowledge transfer from research universities to undergraduate innovation education. Curricular responses to Industry 4.0 technologies (smart materials, additive manufacturing, digital twins) remain delayed ^[6], with scarce research projects and deficient student understanding of human-AI collaboration. Teaching modes remain confined to traditional unit process training, lacking embodied experience in complex engineering systems to foster systemic design and collaborative innovation. Evaluation mechanisms retain outcome-focused approaches, failing to drive compound competency development.

As irreplaceable anchors for embodied cognition, engineering practice and innovation education must reconstruct modularized experimental systems by: developing projects integrating digital twins, IIoT, and intelligent controls to cultivate smart-plus equipment integration capabilities; deploying cyber-physical platforms creating industry-relevant challenges to strengthen complex problem-solving skills; and deepening topologically structured university-industry ecosystems to forge engineers possessing both technical innovation and industrial adaptation competencies.

3.Reconstruction Strategies for AI-Empowered Smart Manufacturing Talent Cultivation Systems

3.1 Multidimensional Pedagogical Innovations for Emerging Engineering Programs

The smart manufacturing practice ecosystem confronts structural predicaments: insufficient digitalization in teaching environments, severe generational mismatches between curricula and industrial technologies, fragmented training modules, and systemic disconnects between innovation education and disciplinary training ^[7]. These collectively undermine students' engineering thinking and systemic innovation capabilities in complex industrial scenarios. Breakthrough requires constructing a quad-dimensional intelligent education paradigm—guided by global engineering foresight—that leverages intelligent technology infrastructures, multidisciplinary knowledge graphs, and information fusion platforms to establish progressively advanced capability incubation systems. This framework dissolves barriers between engineering cognition, foundational training, comprehensive practice, and innovation research through cyber-physical integration, enabling progressive development from technical application to systemic integration and original innovation capabilities.

Cross-disciplinary engineering contextualization proves pivotal for reshaping educational value chains. Technology convergence driven by AI fundamentally restructures approaches to solving significant engineering challenges—from

particle physics detection to intelligent diagnostics—demanding transdisciplinary knowledge integration and problem-oriented engineering philosophies^[8]. This necessitates a matrixed curriculum architecture balancing “core technical depth × application scenario breadth”: deep exploration of machine learning architectures and heterogeneous computing systems alongside cultivating abilities to solve complex engineering problems in advanced manufacturing and biomedicine using multimodal analytics. Crucially, comprehensive training across industrial intelligent system lifecycles (concept validation—technical implementation—engineering deployment) must develop architectural thinking for transforming algorithmic advantages into engineering efficacy.

AI-driven educational hubs instigate profound supply-side transformations by dynamically generating multimodal learning pathways. These systems deconstruct learning states in real-time via knowledge graphs, optimize pedagogical strategies using reinforcement learning, and create personalized interfaces through natural language processing. Consequently, learning spaces expand beyond physical classrooms to immersive cyber-physical environments, while instructors evolve from knowledge transmitters to cognitive framework designers. Educators’ core functions now center on designing cross-disciplinary challenge projects, establishing critical discourse mechanisms, and fostering technological ethics, thereby forming symbiotic ecosystems of “AI-guided precision mentoring + educator-led high-order inspiration”.

Lifelong learning capacity reconstruction must transcend spatiotemporal boundaries of traditional engineering education. Rapid knowledge obsolescence in smart manufacturing compels dynamic iteration mechanisms: strengthening STEM core literacy (mathematical modeling, computational thinking, engineering principles) at foundational levels while establishing responsive “technology tracking–knowledge reconstruction–capability transfer” cycles at developmental stages. Educational institutions should collaborate with industries to create professional competency digital twins, developing modularized courses for career phases (e.g., IIoT architect certifications, smart maintenance specialist programs) with blockchain-enabled lifelong credential tracking. Urgent priorities include establishing intelligent learning clouds spanning “academic education–professional development–self-directed advancement” lifecycles to resolve structural contradictions between industrial evolution and human capital upgrading.

Focusing on deep AI-emerging engineering integration in mechanical curricula, this research advances a trinity reform framework (“cognitive leap–scenario reconstruction–evaluation revolution”) grounded in educational ecology theory and OBE-CDIO integration. Systematic paradigm upgrading occurs through knowledge deconstruction, cyber-physical spatial synergy, and data-driven intelligence to create three-dimensional curricular ecosystems merging mechanical frontiers, AI algorithms, and industrial data. This approach dismantles disciplinary barriers, scenario limitations, and unidimensional evaluation, establishing spiral cultivation loops of “theoretical cognition iteration–practical capability progression–innovation capacity regeneration”, thereby providing comprehensive solutions for cultivating interdisciplinary leaders with intelligent system design, industrial algorithm development, and cross-domain collaborative innovation competencies.

Implementation requires elite universities possessing interdisciplinary faculty resources and advanced infrastructure. Strategic priorities include recruiting AI and IIoT-specialized faculty, constructing new engineering-compatible training platforms and innovation bases, and developing next-generation curricula to cultivate talents possessing frontier transdisciplinary knowledge aligned with emerging industrial demands. The following is an introduction to the research plan.

3.2 Innovations in Cyber-Physical Data-Driven Pedagogical Models

3.2.1 AI-Empowered Curricular Reconstruction and Cognitive Transformation

Guided by educational ecology theory, courses including Mechanical Engineering Frontiers, Construction Machinery Structures, and Mechatronic System Analysis & Design undergo tri-dimensional knowledge deconstruction integrating mechanical frontiers, AI algorithms, and industrial data. Modularized AI-infused units establish knowledge graphs spanning complete technical chains from structural design (SolidWorks) and algorithm development (PyTorch) to system integration (ROS). Cognitive constructivism principles inform the design of spiral pedagogical pathways: “cognitive conflict (traditional mechanical design pain points) - conceptual reconstruction (AI intervention) - meaning generation (intelligent system optimization)”. These pathways employ comparative case libraries (e.g., traditional gear design vs. intelligent lifespan prediction) to facilitate students’ transition from experiential to algorithm-enhanced engineers. Industry partnerships

transform industrial-grade AI applications—such as hydraulic pump boom stress prediction models and welding robot mechatronic systems—into configurable teaching packages containing datasets, code libraries, and virtual debugging environments, creating smart conversion channels connecting industrial challenges with teaching cases and research topics.

3.2.2 Immersive Cyber-Physical Learning Scenarios

Hybrid physical-virtual-cloud experimental spaces integrate industrial robot workstations (KUKA KR AGILUS), intelligent sensor networks (NI CompactDAQ), and cloud-based digital twin platforms (ANSYS Twin Builder). This infrastructure enables comprehensive experimentation encompassing physical device manipulation, virtual parameter optimization, and AI algorithm validation. Leveraging 5G-MEC edge computing facilitates real-time remote access to smart production lines, establishing “classroom-as-workshop” environments where operational data becomes teaching material. Smart equipment maker marathons challenge students with autonomous AGV development, intelligent sorting system optimization, and predictive maintenance algorithm design. Discipline competitions (e.g., China National Mechanical Innovation Design Competition) are deeply integrated into curricula and form closed-loop innovation cultivation through “competition-as-practice”.

3.2.3 Data-Driven Precision Assessment Systems

A tripartite data acquisition framework combines classroom behavior capture (MegEye), operational logging (LabVIEW), and code quality analysis (GitHub Copilot). Multidimensional evaluation matrices assess knowledge mastery, skill proficiency, and innovation maturity. BERT NLP models parse lab reports, ResNet CNNs evaluate design drawings, and LSTM networks track learning trajectories to generate 3D capability radar charts quantifying mechanical design, algorithm application, and system integration competencies. AI-powered diagnostic systems deploy reinforcement learning to recommend personalized learning paths (e.g., PyTorch micro-courses for algorithmically challenged students), forming smart improvement cycles: “data collection- problem diagnosis- resource provision- outcome verification”.

4. Implementation Pathways and Case Studies for Industry-Education Integration

4.1 Practice Cases in Emerging Engineering Smart Manufacturing Programs

4.1.1 Designing Industry-Education Fusion Mechanisms

Smart manufacturing pedagogical innovation necessitates coupling paradigms where industrial knowledge topologically feeds into classroom cognition. This involves deconstructing traditional unidirectional instruction models to establish a three-phase evolutionary framework: “industrial problem anchoring-knowledge graph restructuring-intelligent guided deconstruction”. Implementation pathways include leveraging genuine technical pain points (e.g., digital twin latency bottlenecks, multi-robot path planning conflicts) as cognitive triggers to scaffold bidirectional mapping between industrial challenges and technical principles. Instructors function as knowledge architects, constructing multi-tiered deconstruction-reconstruction chains using cognitive scaffolding theory—embedding core principle explanations during industry-induced cognitive conflicts, then guiding students to crystallize innovative solutions through collective intelligence crystallization. Crucially, emerging technologies like edge computing optimization and industrial visual recognition are deeply integrated, forming closed-loop cognitive evolution from technical pain points through theoretical penetration to solution iteration.

Innovative multidimensional feedback systems critically enable mechanism implementation. Quadripartite assessment frameworks comprise: (1) knowledge absorption evaluated through modular conceptual modeling tasks requiring multiscale abstraction of IIoT architectures; (2) technical integration validated via open challenges (e.g., designing cyber-physical plant scheduling systems assessing multimodal data fusion); (3) innovation mindset appraised via technological foresight analyses (e.g., predicting cloud-edge-device continuum trends); (4) engineering ethics examined through technical decision sandbox simulations. These constructs form capacity matrices spanning “conceptual construction-system realization-frontier exploration-ethical deliberation”, uniquely transcending standardized answers to cultivate systemic comprehension of industrial intelligence complexity.

Reform validation requires dynamic competency mapping models synthesizing formative and summative evaluations. Granular-level behavioral data constructs personal knowledge heatmaps via NLP analysis of conceptual linkage strength in

discussions; meso-level digital competency twins track cognitive trajectory evolution from design to prototyping; macro-level structured clinical examinations interrogate systems thinking depth during complex scenarios like industrial digital twin diagnostics. This cross-paradigm assessment integrates cognitive neuroscience, industrial intelligence, and psychometrics, fundamentally elevating evaluation dimensions from knowledge replication to innovation literacy.

4.1.2 Core Course Transformation through AI Empowerment

Smart manufacturing curricular reconstruction requires dynamic industrial technology response mechanisms. The Mechatronic Intelligent Systems course employs engineering machinery hydraulic seal failure prediction as its pedagogical vehicle, guiding students to develop spatiotemporal feature-decoupling models using >300,000 operational IoT data samples. This involves creating leakage prediction architectures integrating LSTM memory units with causal CNNs while simultaneously quantifying environmental impact across equipment lifecycles. The Sustainable Design of Intelligent Equipment course pioneers multi-objective optimization frameworks: deploying AGV transport simulations in digital twin environments, students design metaheuristic scheduling algorithms concurrently optimizing throughput (≥ 35 units/h), carbon intensity ($\leq 0.1 \text{ kgCO}_2/\text{unit}$), and workstation load dispersion ($\leq 15\%$). This paradigm has yielded 17 industrial solutions, including a logistics system using enhanced genetic algorithms that reduced warehouse energy consumption by 22.3%.

Industry-academia knowledge exchange achieves educational value amplification via dual mentorship: industry experts lead 40% of ROS Industrial Robotics Control modules, transforming 12 cases (e.g., reducer vibration spectrum analysis) into contextualized units. The precision manufacturing philosophy training system integrates quantum sensing and multiphysics simulations to meet welding deformation tolerances ($\leq 0.01 \text{ mm}$). Over three years, this reform generated 39 technological feedback instances, including a deep learning weld defect detection system boosting production line yield to 98.7%, winning the China Graduate Robot Innovation Design Championship.

Constructing dynamic assessment networks addresses pedagogical stagnation. For technologically outdated content like tool design, technology evolution mapping methodology is developed: using diamond-coated tool plasma deposition as cognitive anchors, knowledge transfer chains connect material genomics, interface bonding mechanisms, and intelligent monitoring. Three-dimensional evaluation reforms include: micro-level assembly process quantification via motion-capture heatmaps; meso-level smart line failure root-cause analysis assessing multisource data fusion; macro-level digital portfolios tracking cognitive transition trajectories from TRIZ-based conceptualization to digital twin verification. Supporting teacher evaluation digital twins monitor 12 dimensions—from industrial knowledge coverage to emerging technology responsiveness—forming closed-loop quality improvement through “monitoring-diagnosis-enhancement”.

4.2 Implementation Efficacy, Guarantee Mechanisms, and Scalable Value

To address smart manufacturing talent cultivation challenges, we established a dual-track “technological-value” co-education mechanism, creating replicable reform paradigms. The industrial spirit substantiation approach effectively resolves disconnected ethical indoctrination. Specific implementations include: high-speed train gearbox AR courses (annually serving 3,000 students) triggering holographic displays of technological breakthroughs upon component scanning, transforming historical innovations into immersive experiences; and ethics decision sandboxes ($\leq 0.08 \text{ s}$ latency) deployed via the National Supercomputing Center, generating “quality responsibility reports” during hydraulic system debugging to bridge ethical principles and practice. Empirical evidence confirms efficacy: density of responsibility/innovation terminology in lab reports increased from 3.2 to 5.3 instances per thousand words with 100% safety lock compliance.

High-caliber faculty remain pivotal for elite innovation cultivation. We formed a distinguished mentor cohort comprising 30+ professors implementing student-teacher intensive interaction through academic advisory roles, core/advanced course instruction, and undergraduate research supervision. This enables direct student exposure to academic excellence and research frontiers, fostering mutual understanding while integrating promising students into research teams early, creating a two-way empowerment ecosystem between exceptional mentors and protégés.

Within emerging engineering contexts, we constructed a distinctive practice framework centered on quality smart manufacturing experiential learning. This system integrates engineering intuition, competency development, and quality education, implementing continuous research-based learning throughout four-year curricula. Key initiatives include: engaging

students with challenging engineering problems through participation in cutting-edge research and corporate innovation; establishing national smart manufacturing platform access mechanisms for undergraduates; and embedding students into major research/engineering projects. This transforms disciplinary advantages into educational strengths, achieving progressive dimensionality expansion from isolated tasks to systemic engineering perspectives while catalyzing transformative impacts. Digital intelligence technologies enable authentic personalized learning. Deeply integrating AI with educational principles creates high-efficiency learning ecosystems: platforms generate precise learning profiles through behavioral analytics, identifying preferences and difficulties to underpin personalized recommendations; machine learning optimizes resource taxonomies and retrieval efficiency within knowledge bases; and state-resource alignment achieves exact matches between learner states and adaptive materials.

Conclusion

The emerging engineering paradigm demands enhanced practical pedagogy for cultivating smart manufacturing innovators. Guided by the “practice-driven innovation” philosophy, this research integrates engineering praxis into curricular transformation, establishing a multidisciplinary competency-oriented framework emphasizing scientific acumen and engineering literacy. To ensure the continuous development of professional intuition, core competencies, and quality education throughout four-year programs, we constructed industry-academia-research integrated innovation platforms to persistently stimulate creative thinking. Simultaneously, redefining practical education connotation and methodology while innovating evaluation systems comprehensively ensures knowledge-capability-literacy development, elevating smart manufacturing pedagogical quality. Ultimately, this transformation fosters self-directed learning, proactive practice, and innovation pursuit, achieving the integrated cultivation goals of value guidance, knowledge exploration, capability advancement, and literacy enhancement.

Synthesizing international “digitalization and contextualization” best practices while overcoming domestic “disciplinary fragmentation and industry-education disconnection,” our “classrooms-connected-to-workshops” educational model achieves deep convergence of education, industry, and innovation chains. This approach provides an empirical paradigm for distinctive emerging engineering development, accelerating China’s strategic transition from manufacturing power to intelligent manufacturing leadership. Future efforts will refine curricula and faculty development for intelligent manufacturing engineering and smart vehicle engineering programs, steadfastly pursuing multidisciplinary fusion across computing, automation, and mechanical engineering to cultivate interdisciplinary innovators capable of designing, producing, operating, and researching intelligent products and equipment at advanced levels.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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