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Intelligent Manufacturing Revolution: Innovation Practices of High-Skilled Talents in the Digital Transformation Era

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Abstract: The global manufacturing industry is accelerating its digital transformation, while China's intelligent manufacturing faces structural reshaping of high-skilled talents and innovation challenges. Through extensive research, this study analyzes and summarizes specific directions for talent demand and development pathways under intelligent manufacturing, while profoundly revealing the practical dilemmas encountered by China's skilled workforce in innovation practices. The research indicates that digital transformation essentially constitutes knowledge system reconstruction, requiring the establishment of collaborative mechanisms integrating technological convergence, institutional innovation, and cultural incentives to promote systematic industrial upgrading in manufacturing.

Keywords: Intelligent manufacturing; Talent dilemma; Skill innovation; Industrial upgrading

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1. Introduction

The global manufacturing sector is undergoing the fourth industrial revolution. A 2023 McKinsey report reveals that 67% of global manufacturing enterprises have entered the implementation phase of digital transformation [1]. Against this backdrop, China's "Intelligent Manufacturing Development Plan (2021–2035)" issued by the Ministry of Industry and Information Technology (MIIT) explicitly states that by 2025, over 70% of above-scale manufacturing enterprises should complete intelligent transformation [2]. While this target appears nominally achievable, substantial difficulties and challenges persist in practical implementation [3]. The core of this transformation lies in posing unprecedented challenges to high-skilled talents, with the deep integration of traditional skills and digital technologies emerging as a crucial research subject.

2. Technological characteristics and talent requirements of digital industrial transformation

2.1. Technological architecture of intelligent manufacturing systems

Intelligent manufacturing systems exhibit three technological characteristics: "data-driven operation, cyber-physical integration, and autonomous decision-making" [4]. Their core architecture comprises three pillar technologies—Cyber-Physical Systems (CPS), Industrial Internet of Things (IIoT), and Artificial Intelligence (AI)—which have directly restructured production processes and talent competency frameworks.

(1) Deep Integration of CPS

Siemens' Amberg Digital Factory (EWA) utilizes digital twin technology to connect 2,300 sensors in physical workshops with virtual models in real time [5], achieving full-process digitization from order placement to product delivery. 2022 data shows that the factory's product defect rate in certain processes has dropped to 11 ppm [6], with a 30% shorter production cycle compared to traditional models. This transformation demands technicians to possess "physical-digital dual-space operational capabilities." For instance, fitters assembling precision components must simultaneously operate CNC machine tools and parameter calibration systems on digital twin platforms.

(2) Vertical Integration of IIoT

Sany Heavy Industry's "No. 18 Plant" employs 5G+IIoT technology to connect over 2,000 devices to an industrial internet platform [7]. Workers using handheld terminals can access real-time equipment status data, improving maintenance response speed by 60% [8]. In this context, traditional equipment maintenance skills must evolve into "predictive maintenance capabilities," requiring technicians to master digital diagnostic technologies such as vibration analysis and thermal imaging monitoring.

(3) Ubiquitous Application of AI-Assisted Decision-Making

General Electric's (GE) aircraft engine assembly line incorporates machine learning algorithms to automatically detect anomaly patterns in millions of assembly data points [9]. By 2024, this production line achieved 99.97% assembly accuracy [10], reducing manual re-inspection workload by 85%. This imposes new requirements on quality inspectors: they must possess "AI misjudgment correction capabilities," combining an understanding of algorithmic logic with practical experience to optimize model parameters.

2.2. Emerging skill demand matrix

Building on the World Economic Forum's concept of "Skill Half-Life" [11], this study constructs a high-skilled talent demand matrix for the manufacturing sector (**Table 1**).

Table 1. Emerging skill requirements for high-skilled talents: Case studies

Traditional skill dimension	Digital empowerment requirements	Typical corporate practice cases
Mechanical assembly capability	Digital twin system operation	CRRC High-Speed Rail Bogie Assembly Line: Workers use AR glasses to access virtual assembly guidance, achieving ± 0.01 mm positioning accuracy
Process optimization capability	Big data analytics application	XCMG Hydraulic Cylinder Production Line: Analyzed 120,000 machining datasets via Minitab, optimized boring parameters to increase yield rate by 15%
Quality inspection capability	Machine vision integration	Haier Air Conditioner Compressor Line: AI vision system achieves 0.8-second/item detection speed, manual re-inspection rate reduced to below 3%
Equipment maintenance capability	Predictive maintenance technology	Shenyang Machine Tool i5 Smart CNC: Using vibration sensor data to train failure prediction models, downtime reduced by 40%
Process design capability	Topology optimization algorithm application	CASC Satellite Bracket Project: ANSYS-based topology optimization increased material utilization rate from 65% to 92%

Digital technologies empower traditional craftsmanship, with skill transformation pathways demonstrating three key characteristics: "digitization of tools, intellectualization of processes, and data-driven decision-making."

(1) Impact of tool digitization on operational levels

At Tesla's Shanghai Gigafactory die-casting workshop, traditional manual filing has been replaced by a 3D scanning-robotic correction system. Workers must master handheld 3D scanner operations, capable of completing data collection and deviation analysis for 2 m^2 components within 10 minutes. This transformation converts "filing tactile experience" into quantifiable digital tolerance standards.

(2) Reconstruction of process intellectualization at technical levels

In diesel injector manufacturing, Bosch Group has encoded master craftsmen's "grinding tactile experience" into AI control parameters. By collecting 1,200 hours of operational data from 56 senior technicians, a dynamic process optimization model was developed, shortening new product development cycles by 22 days (Fraunhofer Institute, 2022). This demands technicians' "experience digitization capability" to transform tacit knowledge into programmable process parameters.

(3) Penetration of data-driven decision-making at strategic levels

Komatsu's intelligent welding system automatically generates process improvement plans by analyzing correlations between historical welding data and product failure rates. The decision-making paradigm has shifted from "experience-driven" to "data + experience" dual-drive, requiring technicians to master data analysis tools such as SPC (Statistical Process Control).

2.3. Structural shift in skill demand

A 2024 manufacturing talent survey reveals that digital transformation drives the emergence of "Triple Growth-Triple Decline" characteristics in skill demand (**Figure 1**) [12].

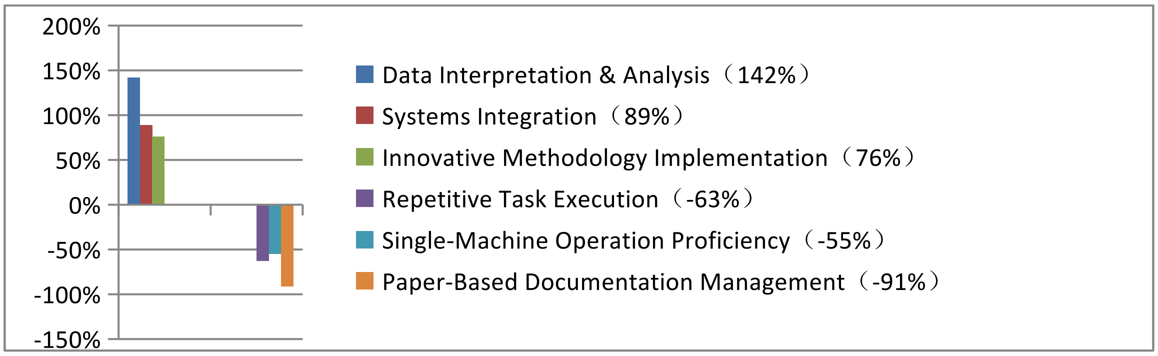

Figure 1. Manufacturing skill demand evolution (2018–2024)

3. Real-world dilemmas in innovation practices

3.1. Multidimensional manifestations of competency gaps

A 2022 survey by China's Ministry of Human Resources and Social Security (MHRSS) revealed a "bimodal distribution" in the high-skilled manufacturing workforce [13]: technicians aged 45+ account for 58%, while young workers aged 25–35 constitute only 19%. This age gap creates overlapping contradictions in skill inheritance and digital transformation. For example, at a defense industry enterprise specializing in precision guideway assembly, senior technicians can achieve a scraping accuracy of 0.002 mm through tactile experience but struggle to operate laser tracking measurement systems. Conversely, younger technicians proficient in using coordinate measuring machines lack an intrinsic understanding of fit tolerances. This "craftsmanship digitization" competency gap fundamentally stems from barriers in converting tacit knowledge to explicit knowledge.

A deeper contradiction lies in the lagging skill evaluation system. The current National Occupational Skill Standards predominantly focus on traditional skills as core assessment criteria, lacking evaluation standards for emerging competencies such as CAD reverse engineering and digital twin system operation.

3.2. Systemic impacts of institutional barriers

At the innovation commercialization stage, a "valley of death" phenomenon persists. A 2023 survey of a state-owned enterprise showed that only 12% of worker proposals from its "Five Small Innovations" program progressed to industrialization. The root obstacle is the absence of market-oriented commercialization mechanisms: enterprises classify innovation outcomes as job-related inventions, offering inventors only symbolic rewards, while skilled workers lack capabilities in patent applications or technology equity participation. In a case involving high-speed rail brake system improvements, a fitter team developed an intelligent pre-tensioning device that tripled maintenance intervals. However, disputes over intellectual property ownership prevented its adoption as a technical standard.

A more severe challenge arises from organizational cultural inertia. A comparative study of a German-funded enterprise revealed that workers at its Chinese subsidiary propose an average of 0.7 improvement suggestions per year, only one-fourth of those at its German headquarters. Cultural differences manifest in Germany's "trial-error budgets" supporting unconventional innovation, whereas most Chinese enterprises still adhere to rigid "results-oriented" evaluation systems.

4. Innovation practices of China's high-skilled talents

Innovation in traditional skills has become imperative, evolving through a "technological convergence–methodological renewal–value reconstruction" logic. This innovation transcends mere digital tool adoption, instead requiring deep restructuring of traditional craftsmanship's knowledge systems and practical paradigms. A methodology with Chinese characteristics is gradually emerging through these practices.

The satellite bracket assembly project by China Aerospace Science and Technology Corporation (CASC) exemplifies technological convergence [14]. Traditional titanium alloy milling for satellite brackets faced long processing cycles (72 hours average) and low material utilization (< 40%). The team integrated core fitter assembly techniques with additive manufacturing, innovating a topology optimization design:

Conducted mechanical simulations using ANSYS to identify critical load paths.

Fabricated lightweight structures via Selective Laser Melting (SLM) 3D printing.

Leveraged fitters' precision adjustment skills for micron-level assembly.

This hybrid "digital design + additive manufacturing + manual refinement" model [15] reduced bracket weight from 12.3 kg to 7.4 kg and elevated modal frequency to 153 Hz, meeting stringent satellite orbital requirements. The case demonstrates high-skilled talents' convergence capabilities in three dimensions: deep understanding of traditional processes, adaptive selection of digital technologies, and cross-technology integration innovation.

SAIC Volkswagen's new energy vehicle battery case assembly project showcases human-machine collaborative innovation. Facing a 0.05 mm assembly tolerance requirement for 21700 battery modules, traditional fixture-dependent methods achieved only 82% qualification. The team introduced an AR-assisted "virtual-physical mapping–intelligent guidance–error compensation" solution:

HoloLens2 superimposed digital twin models onto physical workpieces for real-time assembly state comparison.

Machine learning algorithms optimized assembly paths using historical data.

Fitters performed final gap adjustments.

This "digital guidance + human decision-making" hybrid intelligent mode reduced assembly time from 2 hours/unit to 40 minutes/unit with zero-defect delivery. The practice reveals that high-skilled talents' innovation value now lies in value judgment and decision optimization within human-machine collaboration, rather than mere operational execution.

5. Exploration of innovation development pathways

Amid profound global manufacturing restructuring [16], industrial advancement requires systemic transformation across four dimensions: technological breakthroughs–industrial synergy–green intelligent manufacturing–global layout.

5.1. Dual-driven strategy: Core technology breakthroughs and digital transformation

The machinery industry must establish a full-chain innovation system spanning "base materials–core components–intelligent equipment." For instance, Sany Heavy Industry achieved 95% localization of intelligent excavator core components through self-developed hydraulic systems and controllers. Simultaneously, its cloud platform connects 220,000 devices, enabling full lifecycle digital services. Key strategies include:

(1) Prioritizing foundational technologies: Establish industry R&D platforms to jointly tackle high-precision servo motors and high-temperature-resistant bearing steels.

(2) Advancing digital twin applications: Deeply couple physical equipment with digital models to shorten design validation cycles and reduce maintenance costs.

(3) Cultivating industrial software ecosystems: Learn from Supcon's DCS breakthroughs to develop CAE simulation and MES systems, addressing "hardware-software coordination" challenges.

5.2. Vertical integration and cluster synergy

Amid global supply chain reconfiguration, enterprises must build autonomous industrial ecosystems through vertical-depth and horizontal collaboration. CATL's lithium-ion equipment practices offer guidance:

(1) Vertical integration: Control upstream lithium resources, deploy downstream battery recycling, and self-develop coating/winding machines, forming a closed-loop system that cut equipment procurement costs by 30%.

(2) Horizontal clustering: XCMG-led "Jiangsu Construction Machinery Cluster" integrates 2,000+ suppliers under a "prime manufacturer + modular supplier" model, improving supply chain responsiveness by 50%.

5.3. Green intelligent manufacturing system construction

Carbon reduction must permeate "product–process–factory" lifecycles:

(1) Clean product innovation: Dongfang Electric's hydrogen fuel cell powertrain achieves 350 Wh/kg

energy density, reducing emissions by 90% vs. diesel.

(2) Low-carbon process retrofits: CITIC Heavy Industries' electric arc furnace short-process steelmaking slashed energy consumption from 580 kgce/t to 280 kgce/t, with waste heat recovery boosting energy efficiency by 40%.

(3) Zero-carbon factories: Sany's Beijing Lighthouse Factory cut energy intensity per output unit by 76% via photovoltaics, smart microgrids, and digital energy management.

5.4. Global collaborative innovation networks

Shift from product exports to technical standard exports:

(1) International standardization: CRRC's ISO 22163 rail standards globalized Chinese high-speed rail welding and damping specifications, enabling entry into 109 countries.

(2) Localized R&D centers: Follow Weichai Power's model of establishing overseas innovation hubs (e.g., Germany's new energy R&D center).

(3) Service-oriented manufacturing exports: Sany's Brazil "equipment leasing + remote operation" model raised utilization by 20% via IIoT-enabled real-time diagnostics.

6. Conclusion

The global manufacturing digital transformation is driving profound restructuring of industrial value chains, rooted in the deep integration of traditional manufacturing knowledge systems with digital technologies. Research indicates that intelligent manufacturing not only revolutionizes technological architectures but also triggers structural shifts in talent competency matrices—data-driven decision-making replaces experience-guided operations, and human-machine collaboration supersedes singular skill applications, marking a paradigm shift from "craftsmanship inheritance" to "knowledge reconstruction." China's manufacturing upgrade requires systemic breakthroughs across knowledge production, dissemination, and application to secure a commanding position in global value chain restructuring, ultimately achieving the leap from a "manufacturing powerhouse" to an "intelligent manufacturing leader."

Disclosure statement

The authors declare no conflict of interest.

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