



A Human–Machine Complementary Education Model for Highly Skilled Talent in Smart Manufacturing

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Abstract. This study addresses the trend in intelligent manufacturing jobs shifting from routine operations to equipment maintenance, fault diagnosis, and cross-system collaboration, and explores an observable and evaluable pathway for human-machine complementary talent cultivation. Based on questionnaires, field visits, and interview data collected by the research team from 23 intelligent manufacturing enterprises in Beijing, the study organizes job demands and competency gaps. 83% of the surveyed enterprises reported a decrease in recruitment for basic operation positions, while 74% reported an increase in demand for equipment operation and maintenance and technology application positions; the score gaps between demand and current status for cross-disciplinary knowledge integration, fault diagnosis and problem solving, and data analysis and intelligent decision-making were 1.31, 1.26, and 1.13 points, respectively. On this basis, a TBMHP (Technology-Business-Management-Humanity-Psychology) five-dimensional competency model was constructed, a three-stage progressive cultivation system of “competency integration—competency training—competency enhancement” was proposed, and a cross-disciplinary integrated curriculum architecture of “foundational sharing + intermediate integration + advanced cross-selection” was designed. The study argues that the core of human-machine complementarity lies in achieving a complete educational closed loop from “knowledge construction” to “skill acquisition” and then to “literacy development.” This model provides an actionable practical pathway for higher vocational colleges to address the challenge of “machine replacing humans.”

Keywords: Additional Keywords and Phrases: smart manufacturing, vocational education, human–machine complementarity, competency model, competency assessment

1 Introduction

A new round of industrial transformation and upgrading, represented by “machine replacing humans,” is gradually deepening in global manufacturing. The robot and intelligent manufacturing industry in the Beijing Economic-Technological Development Area achieved an output value of 82.04 billion yuan, and the demand for industrial robot commissioning positions has grown at an average annual rate of 30%. Meanwhile,

by the end of 2025, the talent gap in the intelligent manufacturing field is expected to reach approximately 4.5 million people. The core of this supply-demand contradiction lies not in a shortage of talent quantity, but in a mismatch of competency structure: what enterprises need is no longer technical workers capable of performing standardized operations, but composite talents capable of fault diagnosis, system optimization, and cross-domain collaboration in human-machine collaborative environments.

However, the existing vocational education system appears inadequate in responding to this change. Workers with single skills face a serious threat of unemployment, while composite talents with cross-disciplinary advantages will become the mainstream of the market [1]. Research on the risk of technological substitution reminds us to focus on task structure rather than simply inferring the disappearance of entire occupations [2]. Existing studies have suggested that skill talent cultivation in the intelligent manufacturing industry should be based on job demands, focus on intelligent manufacturing skill-related courses, and cultivate the ability to address complex problems [3-5]. In the survey, 52.2% of enterprises believed that curriculum content is clearly disconnected from enterprise technological development, and 60% of enterprises considered that graduates' "lack of frontline practical experience" is the biggest obstacle to employment. The root of the problem lies in the fact that the traditional cultivation model narrows "competency" to "skills" and equates "cultivation" with "training," neglecting the complete educational chain from knowledge construction to literacy development.

Based on empirical enterprise research, this paper reveals the structural transformation pattern of competency demands for high-skilled talents in the context of "machine replacing humans," proposes a TBMHP five-dimensional competency model and a three-stage progressive cultivation model of "competency integration—competency training—competency enhancement," and expands competency cultivation from flat skill training to a three-dimensional process of literacy generation. The research objectives include: identifying competencies that enterprises consider important but for which graduates are relatively underprepared, proposing a cultivation structure that matches tasks, and providing actionable indicators for subsequent effectiveness evaluation.

2 Enterprise Demand and Competency Gaps

2.1 Job Structure in the Surveyed Enterprises

The project team investigated 23 smart manufacturing enterprises in Beijing, especially in the Beijing Economic-Technological Development Area, covering advanced manufacturing, automotive manufacturing, and integrated circuits. The reported organizations included multinational firms such as SMC China, Bosch Rexroth, and Siemens China, as well as domestic manufacturers including BOE and NAURA Technology. Figure 1 reproduces the industry and size composition; the counts corresponding to the reported percentages are 17, 4, and 2 by sector and 10, 6, and 7 by firm size, respectively.

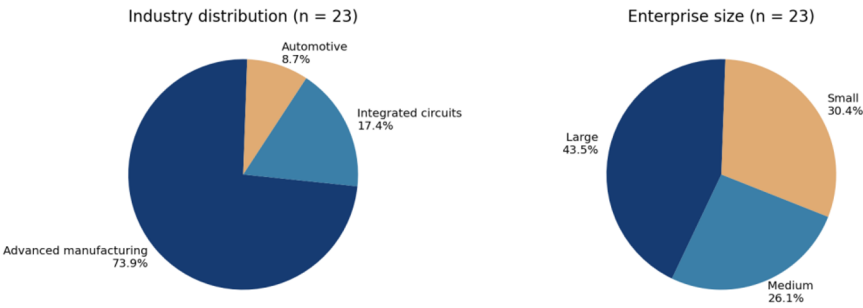


Fig. 1. Industry and size distribution of the 23 surveyed enterprises.

The inquiry indicates falling demand for routine operating jobs and rising demand for jobs combining technology and system knowledge. Table 1 presents the directional changes reported in the source manuscript. The project additionally cites national year-on-year increases of 54.85% for robot commissioning engineer vacancies and 22.16% for industrial robot engineer vacancies, as well as annual demand growth of 30% for commissioning work. Within the 23-firm inquiry, 83% reported a noticeable decrease in recruitment for basic operating jobs during the preceding three years and 74% reported a substantial increase in maintenance and technical application positions. One automotive human-resources manager described a line moving from approximately 20 operators to three or four technicians responsible for maintenance and commissioning after automation. This is an illustrative respondent account, not a general staffing ratio.

Table 1. Reported trends in job demand under manufacturing automation.

Job category	Reported trend	Typical position	Main driver
Basic operations	Marked decrease	Line operator; basic assembler	Replacement of repetitive manual tasks
Equipment maintenance	Rapid increase	Robot commissioning engineer; maintenance technician	More automated equipment to maintain
Technical application	Sustained increase	PLC programmer; automation engineer	Smart production-line upgrades
System integration	Gradual increase	Smart-line architect; MES engineer	Coordination across machines and systems
Data analysis	Emerging increase	Industrial data analyst; AI application engineer	Data-supported manufacturing decisions

2.2 Competency Priorities and Gaps

Enterprises rated the importance of core competences on a five-point scale. The three highest mean ratings reported in the source were equipment operation and commissioning (4.61), fault diagnosis and problem solving (4.52), and interdisciplinary knowledge integration (4.35). Figure 2 presents the eight mean values that can be read consistently from the source chart.

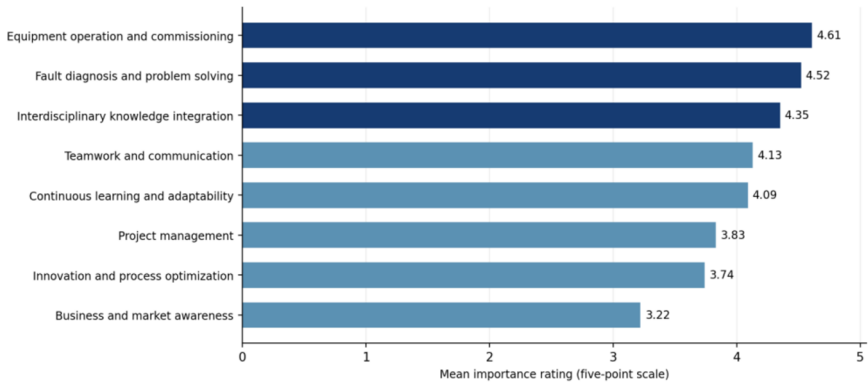


Fig. 2. Enterprise importance ratings for eight core competencies (five-point scale).

A second comparison considered the difference between employer demand ratings and reported ratings of graduates' current capability. The largest gaps were interdisciplinary knowledge integration (1.31), fault diagnosis and problem solving (1.26), and data analysis and intelligent decision-making (1.13), as reported in Table 2. Such a gap is a descriptive subtraction on the reported scale, not a measure of causal impact. It suggests a priority for interdisciplinary troubleshooting and data-informed action, but does not establish that machines can never perform these activities.

Table 2. Reported gaps between enterprise requirements and graduate preparation.

Competency	Demand	Graduate rating	Gap	Rank
Interdisciplinary knowledge integration	4.35	3.04	1.31	1
Fault diagnosis and problem solving	4.52	3.26	1.26	2
Data analysis and intelligent decision-making	4.22	3.09	1.13	3
Innovation and process optimization	3.74	2.70	1.04	4
Project management	3.83	2.91	0.92	5
Continuous learning and adaptability	4.09	3.22	0.87	6
Teamwork and communication	4.13	3.43	0.70	7
Equipment operation and commissioning	4.61	4.09	0.52	8

3 Construction of the TBMHP Competency Model

The TBMHP model describes five dimensions of highly skilled talent: technology (T), business (B), management (M), humanity (H), and psychological capacity (P). Technology encompasses technological understanding and application, innovation, technical operation, and data analysis. Business includes business analysis, market strategy, project management, and negotiation. Management concerns project planning, team coordination, resource allocation, and performance feedback. Humanity emphasizes

cross-cultural communication, teamwork, leadership, and social responsibility. Psychological capacity includes critical thinking, decision-making, resilience, and self-awareness. Figure 3 shows the framework with all five dimensions and their four components.

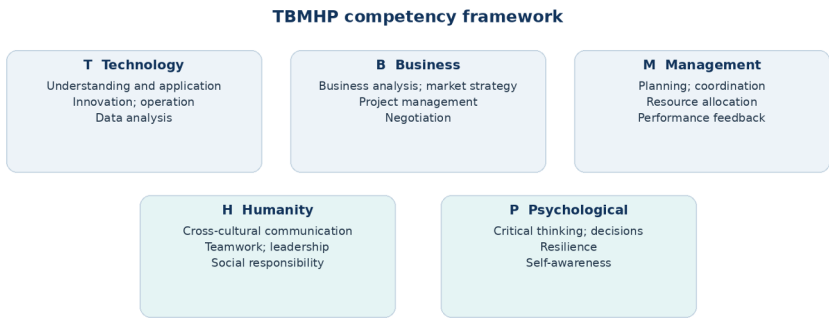


Fig. 3. TBMHP competency framework.

Each dimension is subdivided into four sub-competency items, totaling 20 sub-competency items, and a three-level evaluation rubric (Excellent/Competent/Basic) and core observation points have been established, as shown in Table 3. The theoretical significance of this model lies in its translation of “human irreplaceability” from an abstract proposition into actionable competency standards. Through the behaviorally anchored rating method, abstract competency indicators are transformed into observable and quantifiable teaching behaviors, such as “fault troubleshooting accuracy,” “number of solution improvement points,” and “decision-making accuracy,” thereby moving competency cultivation from “intuition-based” to “measurable.”

Table 3. Evaluation Indicators and behavioral anchors for Each Dimension of the TBMHP Competency Model

Table 3a: TBMHP behavioral anchors for Technology (T).

Subcompetency	Advanced (90–100)	Competent (75–89)	Foundational (60–74)	Core observation
Understanding and application	Independently resolves complex technical problems and recognizes new technologies	Performs standardized operations and understands basic principles	Completes basic operations with guidance	Fault diagnosis accuracy; process-parameter optimization
Technological innovation	Proposes original solutions or patentable ideas	Suggests improvements to existing technologies	Understands and reproduces established innovation cases	Number of improvement proposals; patents or papers
Technical operation	Operates precisely, at more than 20% above the stated industry efficiency benchmark	Operates safely and proficiently to job requirements	Operates essentially to specification but more slowly	Operation time; product acceptance rate
Data analysis	Builds predictive models and uses them to guide decisions	Cleans and visualizes data using suitable tools	Reads basic data reports	Quality of analysis report; model accuracy

Table 3b: TBMHP behavioral anchors for Business (B).

Subcompetency	Advanced (90–100)	Competent (75–89)	Foundational (60–74)	Core observation
Business analysis	Writes and presents a comprehensive business plan	Prepares a market and competitor analysis	Identifies basic market factors	Logic and evidential support of report
Market strategy	Plans and implements a small marketing campaign independently	Contributes to a product-promotion plan	Understands product positioning	Feasibility of strategy; return on investment
Project management	Coordinates a cross-unit project and delivers on or ahead of schedule	Manages one project and controls time and cost	Assists a project manager with assigned tasks	Schedule delays; cost variance
Negotiation	Leads a negotiation to a mutually beneficial outcome	Prepares materials and supports negotiation	Conducts basic business reception	Negotiation outcomes; client feedback

Table 3c: TBMHP behavioral anchors for Management (M).

Subcompetency	Advanced (90–100)	Competent (75–89)	Foundational (60–74)	Core observation
Project planning and control	Develops a work breakdown structure and Gantt chart and adjusts resources	Develops a simple project plan	Executes an established plan	Plan completion; resource utilization
Team coordination and communication	Resolves conflict and strengthens team cohesion	Communicates instructions and coordinates internal tasks	Reports on assigned tasks	Team climate; communication errors
Resource allocation	Reduces operating cost by more than 10% against a stated baseline through allocation	Allocates personnel, funding, and materials appropriately	Allocates resources under direction	Cost savings; idle resources
Performance assessment and feedback	Designs performance indicators and improvement strategies	Scores and gives feedback using criteria	Collects and organizes performance data	Fairness of assessment; improvement

Table 3d: TBMHP behavioral anchors for Humanity (H).

Subcompetency	Advanced (90–100)	Competent (75–89)	Foundational (60–74)	Core observation
Cross-cultural communication	Coordinates international work and understands cultural norms	Communicates professionally in a foreign language	Conducts basic everyday communication	Participation; communication barriers
Teamwork	Proactively helps colleagues and supports team cohesion	Contributes actively without shifting responsibility	Completes individual assigned work	Team performance; peer rating
Leadership	Motivates a team and guides difficult problem solving	Leads a group of three to five	Allocates basic tasks	Goal attainment; team retention

Subcompe- tency	Advanced (90– 100)	Competent (75– 89)	Foundational (60–74)	Core observa- tion
Social respon- sibility	Integrates social responsibility into design and public service	Recognizes so- cial issues and basic environ- mental duties	Explains the meaning of so- cial responsi- bility	Service hours; safety or envi- ronmental re- view

Table 3e: TBMHP behavioral anchors for Psychological capacity (P).

Subcompe- tency	Advanced (90– 100)	Competent (75– 89)	Foundational (60–74)	Core observa- tion
Critical think- ing	Develops a system- atic alternative to routine practice	Questions a pro- posal and seeks evidence	Separates fact from opinion	Number of jus- tified improve- ments; rigor of argument
Decision-mak- ing	Makes timely, jus- tified decisions un- der pressure	Weights ad- vantages and dis- advantages	Makes routine decisions by protocol	Decision qual- ity and time
Resilience	Recovers promptly and manages emo- tions after setbacks	Continues work under pressure	Struggles to persist when faced with dif- ficulties	Stress-task as- sessment; time on task
Self-awareness	Identifies develop- ment needs and prepares a growth plan	Accepts feedback and reflects on performance	Describes per- sonal strengths and limitations	Plan comple- tion; depth of reflection

4 A Three-Stage Pathway for Human–Machine Complementary Education

Competence integration, competence training, and competence advancement form a sequence from knowledge construction to skill acquisition and then the development of professional qualities. The first stage addresses what learners should study, the second how they should practice, and the third how they can continue to develop. The stages reinforce one another rather than representing three independent interventions. Together, they give each TBMHP dimension a place in curricular work, supervised practice, and workplace-linked reflection.

4.1 Competence Integration through a Cross-Disciplinary Curriculum

Competency integration serves as the starting point of the talent cultivation model and addresses the question of “what to learn.” The proposed architecture has common foundations for all students, shared professional courses across specializations, and cross-disciplinary electives (Figure 4). Common foundations include mechanical drawing, electrical and electronic fundamentals, industrial Internet concepts, and related general education. Shared professional modules cross conventional boundaries, particularly in intelligent control and machine vision. Advanced options include emerging technologies and certificate- or competition-linked work to support more individualized development. The design aims to connect different specializations through the common

TBMHP capability structure rather than merely placing similar majors within one administrative group.

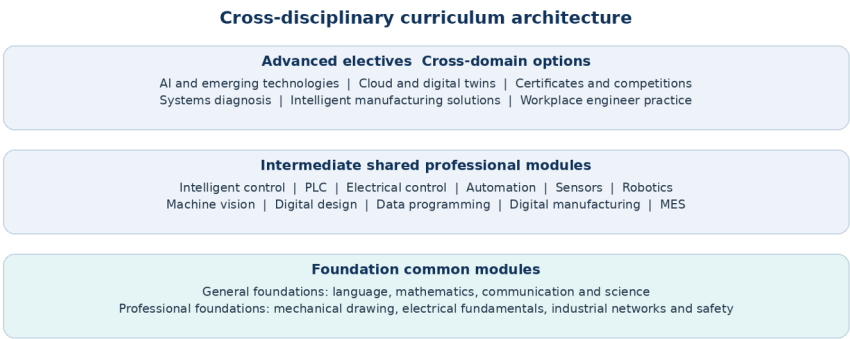


Fig. 4. Cross-disciplinary curriculum architecture with common foundations, shared professional modules, and advanced electives.

4.2 Competence Training on Shared School–Enterprise Platforms

Competency training addresses the question of “how to practice.” The university has collaborated deeply with enterprises such as Yandong Microelectronics, BOE, SMC (China), Bosch Rexroth, and Siemens (China) to build shared platforms including an industrial robot training area, an intelligent production line integration training area, a digital twin simulation area, an industrial network training area, and an intelligent manufacturing comprehensive training area, following the “three-real” principle of “real equipment, real scenarios, and real processes.” Table 4 presents the functional layout of the university-enterprise co-constructed internship and practical training platform.

Table 4. Functions of the shared training platform and associated enterprises in the source manuscript.

Module	Main activities	TBMHP dimen- sions	Associated enterprise
Industrial robotics	Robot operation, program- ming, commissioning, and maintenance	T	SMC China; Bosch Rexroth
Integrated smart line	PLC programming, line integration, and MES op- erations	T, M	BOE; Yandong Microelec- tronics
Digital-twin simu- lation	Virtual commissioning, process simulation, and digital twins	T, P	Siemens China
Industrial network- ing	Industrial Ethernet, fieldbus, and industrial IoT	T, B	Beijing Sifang Automation
Integrated smart manufacturing	End-to-end smart-factory simulation and systems in- tegration	T, M, H, P	BAIC Group

4.3 Competence Advancement with Field Engineers and Emerging Technology

Competency enhancement addresses the question of “how to achieve sustainable development.” By leveraging the skill-orientation advantages of leading enterprises and relying on industry-education integration consortia, advantageous enterprise resources are introduced into the education sector [6]. Relying on the On-site Engineer Alliance mechanism, the research team invites enterprise technical experts and master craftsmen to regularly visit the university to deliver technical lectures and provide project guidance.

At the same time, artificial intelligence technology is deeply integrated into teaching: intelligent tutoring systems enhance students’ competencies by 30% in practical application assessments; virtual simulation and training platforms overcome the limitations of physical equipment; and a big-data-driven dynamic update mechanism for curriculum content increases the relevance of teaching content by 20%. AI-assisted tools can retrieve approved manuals, propose counterexamples, or support low-risk simulations, but they should display sources and versions and preserve the initial records of students’ independent answers. Existing studies have discussed both the potential and the errors and dependency risks of large language models in education [7-8]; therefore, the mere “use of AI” cannot be regarded as teaching effectiveness.

5 Conclusion

This study, based on a systematic survey of 23 intelligent manufacturing enterprises in Beijing, reveals the structural transformation of competency demands for high-skilled talents in the context of “machine replacing humans,” constructs a TBMHP five-dimensional competency model, and proposes a three-stage progressive talent cultivation model of “competency integration—competency training—competency enhancement.” The main contributions of the study are as follows:

At the theoretical level, it transforms “human irreplaceability” from an abstract proposition into an actionable TBMHP competency standard framework, providing a systematic competency reference for high-skilled talent cultivation in the field of intelligent manufacturing.

At the methodological level, it proposes a cross-disciplinary integrated curriculum system of “foundational sharing + intermediate integration + advanced cross-selection,” reflecting a shift in the logic of professional group construction from “merging similar items” to “cross-disciplinary integration.”

At the practical level, it constructs a complete educational loop from knowledge construction to skill acquisition and then to literacy development, providing a replicable practical pathway for higher vocational colleges to address the challenge of “machine replacing humans.”

Follow-up research will expand the empirical validation scope of the TBMHP competency model, explore deeper mechanisms of industry-education integration, and continuously track the impact of artificial intelligence technology development on competency standards.

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