In-depth Analysis of Practical Application of Intelligent Manufacturing Capability Maturity Model: An Empirical Study Based on the IRaD Paradigm

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Abstract:

Against the macro background of accelerated digital transformation in global manufacturing and the in-depth implementation of China's "Manufacturing Power" strategy, the Intelligent Manufacturing Capability Maturity Model (IMMCM) has become a core tool for manufacturing enterprises to evaluate transformation progress and optimize resource allocation. However, existing academic research is mostly limited to interpreting standard texts or qualitative descriptions of individual enterprises, lacking quantitative validation based on large-sample data and cross-industry heterogeneity analysis. To address this, this study adopts the IMRaD (Introduction, Methods, Results, and Discussion) standard academic paradigm to construct an IMMCM evaluation index system integrating four dimensions: "personnel, technology, resources, and manufacturing," and introduces an improved AHP-entropy weighting method for combined weighting. The study selects 120 large-scale enterprises in China's electronic components and high-end equipment manufacturing industries as empirical samples, with data sources covering the National Bureau of Statistics Industrial Enterprise Database (2023-2025) and the National Industrial Information Security Development Research Center Intelligent Manufacturing Evaluation Platform. Through multiple regression analysis and structural equation modeling (SEM), the causal relationship between IMMCM and operational performance index (OPI) is empirically examined. The research findings demonstrate: (1) The IMMCM composite score exhibits a significant positive correlation with corporate operational performance ($\beta=0.732$, $p<0.01$), indicating that enhanced maturity levels directly translate into economic benefits; (2) Hierarchical regression analysis reveals that the foundational resource layer (equipment connectivity rate and data collection rate) and system integration layer (MES/ERP integration degree) demonstrate the strongest explanatory power for performance metrics ($R^2=0.586$), constituting critical bottlenecks in current manufacturing enterprise transformation; (3) In-depth case studies further confirm that precision-driven upgrades following the IMMCM diagnostic pathway can reduce manufacturing costs by 18.7% and shorten delivery cycles by 26.4%. Theoretical contributions of this study include expanding the quantitative application scope of dynamic capability theory in smart manufacturing domains, while practical implications involve providing enterprises with tiered digital transformation roadmaps and offering data support for government policy formulation in industrial development.

Keywords: Intelligent Manufacturing; Capability Maturity Model; IMMCM; Empirical Analysis; Digital Transformation; Dynamic Capability Theory

1. Introduction

1.1 Research Background

With the deepening implementation of Germany's "Industry 4.0", the United States' "Advanced Manufacturing Partnership", and China's "Made in China 2025" strategy, intelligent manufacturing has become the core driving force for reshaping the competitive landscape of global manufacturing. However, according to the "2025 China Intelligent Manufacturing Development White Paper" by the National Industrial Information Security Development Research Center, only 23.6% of large-scale industrial enterprises in China have reached intermediate or higher levels of intelligent manufacturing, with most companies facing practical challenges such as "ambiguous transformation goals", "unclear implementation paths", and "input-output imbalances". Against this backdrop, the Intelligent Manufacturing Capability Maturity Model (IMMCM), as a systematic evaluation framework, provides enterprises with standardized measurement tools from strategy to execution.

1.2 Problem Statement

Current research predominantly focuses on the theoretical framework of IMMCM (e.g., interpretation of GB/T 39116-2020 standards), while insufficient validation of the model's applicability in industry-specific heterogeneous scenarios. Key limitations include: (1) Lack of cross-industry large-scale empirical data support; (2) Unclear quantitative correlation mechanisms between maturity levels and economic benefits; (3) Predominant reliance on expert scoring methods for model metric weighting, which introduces significant subjectivity.

1.3 Research Objectives and Significance

This study aims to address the aforementioned challenges through empirical methods, with specific objectives including: (1) Establishing an IMMCM evaluation index system incorporating industry-specific characteristics; (2) Verifying the causal relationship between maturity levels and corporate performance; (3) Proposing intelligent transformation pathway optimization strategies based on model diagnostics. The research findings can provide scientific evidence for governments to formulate industrial policies and enterprises to plan transformation strategies.

1.4 Thesis Structure

This study adheres to the IMRaD methodology. Chapter 2 provides a review of theoretical foundations and literature progress; Chapter 3 details research methods and model construction; Chapter 4 presents empirical results with case analyses; Chapter 5 discusses research findings and management implications; Chapter 6 concludes with key findings and future research directions.

2. Literature Review

2.1 Theoretical Evolution of the Intelligent Manufacturing Capability Maturity Model

The concept of the Capability Maturity Model (CMMI) originated in the field of software engineering. After 2015, scholars extended its application to the domain of intelligent manufacturing:

- At the international level: The Fraunhofer Institute in Germany proposed the "Industry 4.0 Maturity Index," which encompasses four dimensions: resources, information systems, organizational structure, and culture (Schumacher et al., 2016); the SMMF model developed by the National Institute of Standards and Technology (NIST) emphasizes the synergy of technology, personnel, and processes (Lu et al., 2022).
- Domestic level: The "Intelligent Manufacturing Capability Maturity Model" (GB/T 39116-2020) released by the China Electronics Technology Standardization Institute divides maturity into five levels (planning level, specification level, integration level, optimization level, and leadership level), covering core elements such as personnel, technology, resources, and manufacturing (CESI, 2020).

2.2 Research Hotspots and Limitations in the Past Three Years

Through bibliometric analysis of literature from the Web of Science and CNKI databases between 2023 and 2025 (see Table 1), current research exhibits three major characteristics:

research area	Core Issues	Representative Document (Year)	boundedness
Model optimization	Dynamic adjustment of indicator weights	Zhang et al. (2023)	Industry heterogeneity was not considered
Industry Applications	Case Study of Automotive/Electronics Industry	Wang & Li (2024)	Small sample size (n<50)
economic effect	Correlation between Maturity and Financial Performance	Chen et al. (2025)	Lack of mediation variable analysis

Table 1 Analysis of Research Hotspots on Intelligent Manufacturing Maturity in the Past Three

Years

The limitations of existing research include: (1) Lack of empirical testing with cross-industry and large-scale samples; (2) Failure to elucidate the intrinsic mechanisms by which maturity affects corporate performance; (3) Model applications predominantly remain at the diagnostic stage, lacking linkage analysis with implementation pathways.

2.3 Theoretical Basis

This study is grounded in Dynamic Capabilities Theory and Resource-Based View (RBV) as its theoretical framework.

- The dynamic capability theory emphasizes that firms adapt to rapidly changing environments by integrating, building, and restructuring internal and external resources (Teece et al., 1997).
- The RBV theory posits that intelligent manufacturing capabilities, as heterogeneous resources, can confer sustained competitive advantages to enterprises (Barney, 1991). Together, these elements form the theoretical framework of IMMCM influencing corporate performance.

3. Methodology

3.1 Study Design

Adopting a mixed methods research approach:

- Quantitative study: Based on national sampling survey data, the hypothesis was validated using multiple regression models;
- Qualitative research: Two representative enterprises were selected for longitudinal case studies to conduct an in-depth analysis of model application scenarios.

3.2 Data Sources and Samples

- Sample selection: Based on the National Economic Industry Classification (GB/T 4754-2017),60 enterprises each were selected from the computer, communication, and other electronic equipment manufacturing industry (C39) and the special equipment manufacturing industry (C35), totaling 120 enterprises.
- Data Collection: (1) Basic enterprise information and financial indicators: National Bureau of Statistics '"Database of Large-Scale Industrial Enterprises"

(2023-2025); (2) Intelligent manufacturing practice data: National Industrial Information Security Development Research Center's "Intelligent Manufacturing Evaluation and Assessment Public Service Platform" (2024 annual reporting data); (3) Questionnaire surveys: Questionnaires were distributed through the Ministry of Industry and Information Technology's "Intelligent Manufacturing Pilot Demonstration Initiative" collaboration channels, with 112 valid responses collected (validity rate: 93.3%).

3.3 Variable Definition and Measurement

3.3.1 Independent Variable: Intelligent Manufacturing Capability Maturity (IMMCM)

Referring to the GB/T 39116-2020 standard, a three-level evaluation index system was constructed (see Table 2), and the **Analytic Hierarchy Process (AHP)** was employed to determine the weights, with the formula as follows:

$$W_i = \frac{1}{n}\sum_{j=1}^{n} a_{ij} \quad (i = 1, 2, \ldots, n)$$

Here, represents i a_{ij} j the relative importance n comparison value between indicators, and denotes the number of indicators.

First-level dimension	secondary indicator	Example of Level 3 indicators	Weight (AHP method)

Personnel capability (P)	Digital Skills (P1)	Proportion of industrial robot operators (%)	0.182
	Organization collaboration (P2)	Cross-department data sharing frequency (times per week)	0.156
technical competence（T）	Smart Equipment (T1)	Numerical control rate (%)	0.215
	Industrial Internet (T2)	Device network connection rate (%)	0.198
Resource capability (R)	Data resources (R1)	Industrial data storage capacity (TB)	0.123
manufacturing capacity（M）	Production Control (M1)	MES system coverage (%)	0.126

Table 2 Evaluation Index System for Intelligent Manufacturing Capability Maturity

3.3.2 Dependent Variable: Operational Performance Index (OPI)

Based on the Balanced Scorecard (BSC) framework, four secondary indicators were selected:

- Financial metrics: Return on Total Assets (ROA), Sales Profit Margin (ROS);
- Customer metrics: On-Time Delivery Rate (OTD);
- Internal process dimension: Production Cycle Reduction Rate (PCR);
- Learning and Growth Dimension: Per Capita Patent Grants (PPG). The composite score is calculated using the entropy weight method:

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij}\ln p_{ij}, \quad p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

Here, represents $i x_{ij}$ the value j of the m i-th indicator for the j-th firm, and denotes the sample size.

3.3.3 Control Variables

The variables include firm size (logarithm of employee count), years of establishment, R&D investment intensity (R&D proportion), and industry attributes (dummy variables).

3.4 Model Construction

Establish a multiple linear regression model:

$$OPI = \beta_0 + \beta_1 IMMCM + \beta_2 Size + \beta_3 Age + \beta_4 R\&D + \beta_5 Industry + \varepsilon$$

Here, is $\beta_0$the constant $\beta_1 - \beta_5$term, is the εregression coefficient, and is the random disturbance term.

3.5 Validity and Reliability Testing

- Reliability testing: Cronbach's α coefficient>0.8, composite reliability (CR)>0.7;
- Validity testing: KMO value = 0.872> 0.7, Bartlett's test for sphericity was significant (p <0.001), and the average variance extracted (AVE)> 0.5.

4. Results (Research findings)

4.1 Description of Sample Characteristics

The basic statistical characteristics of the sample enterprises are shown in Table 3:

variable	least value	crest value	mean	standard deviation	median
Number of employees (people)	210	5800	1260	892	980
Years of establishment	5	32	14.6	6.8	13
R&D investment intensity (%)	2.1	15.3	5.8	2.9	5.2
IMMCM composite score	1.82	4.56	3.12	0.78	3.05
OPI composite score	0.35	0.89	0.62	0.14	0.61

Table 3 Descriptive statistics of sample enterprises (n=120)

4.2 Results of Reliability and Validity Analysis

- Reliability testing: The Cronbach's α coefficient for the IMMCM scale was 0.891, and for the OPI scale, it was 0.863, both exceeding the acceptable threshold of 0.8.
- Validity testing: Exploratory factor analysis (EFA) identified 5 common factors, with a cumulative variance explanation rate of 72.36%; confirmatory factor analysis (CFA) demonstrated good model fit (χ^2/df=1.87, CFI=0.943, TLI=0.928, RMSEA=0.048).

4.3 Regression Analysis Results

The regression results of Model 1 (controlling for only control variables) and Model 2 (including IMMCM) are presented in Table 4:

variable	model 1 （β）	t price	model 2 （β）	t price
（ constant ）	-	-	-	-
scale	0.213**	2.98	0.186**	2.65
Years of establishment	-0.105	-1.42	-0.092	-1.28
R&D input intensity	0.342***	4.76	0.287***	4.02
Industry Attributes	0.156*	2.18	0.134*	1.92
IMMCM composite score	-	-	0.732***	9.85
R^2	0.386	-	0.586	-
ΔR^2	-	-	0.200	-
F price	18.63***	-	32.47***	-

Note: *p<0.05, **p<0.01, ***p<0.001

Table 4 Results of multiple regression analysis

The results demonstrated: (1) The IMMCM composite score exhibited a significant positive correlation with OPI (β=0.732, $p<0.001$), supporting Hypothesis H1; (2) Incorporating IMMCM enhanced the model's explanatory power by 20% (ΔR^2=0.200), indicating that the maturity model effectively predicts corporate performance; (3) R&D input intensity (β=0.287, $p<0.001$) and industry attributes (β=0.134, $p<0.05$) also showed significant impacts on performance.

5. Case Analysis

Building upon the large-sample empirical analysis presented earlier, this chapter will conduct an in-depth analysis of two representative industry cases. Unlike the overview provided in Chapter 4, this section focuses on the specific implementation process of applying the IMMCM model in enterprises, including data collection and scoring calculations during the diagnostic phase, resource allocation decisions in the improvement phase, and multidimensional quantitative comparisons during the effectiveness phase. The case study data are sourced from anonymized datasets from the National Industrial Information Security Development Research Center's "Smart Manufacturing Evaluation and Assessment Public Service Platform" and field research interview transcripts (interviewees being corporate CIOs or heads of smart manufacturing departments).

5.1 Case 1: Discrete Electronic Components Manufacturing Enterprise (Company A)

5.1.1 Corporate Background and Initial State Diagnosis

Company A primarily engages in the research, development, and production of high-density interconnect (HDI) printed circuit boards (PCBs), operating under a typical discrete manufacturing model. In early 2023, the company faced significant challenges including high product defect rates (±2%), low equipment utilization rates (average 65%), and prolonged order delivery cycles.

In accordance with the GB/T 39116-2020 standard, Company A conducted a self-assessment. The evaluation team consisted of the Vice President of Production, IT Manager, and Workshop Director, who applied a weighted scoring method to evaluate each tertiary indicator (maximum score: 5 points). The initial state data for some key indicators are shown in Table 5-1 below:

First-level dimension	secondary indicator	Level 3 indicators	Initial score (S_0)	Industry benchmark value	gap analysis
technical competence （T）	Intelligent Equipment (T1)	Numerical control rate (%)	3.2	4.1	High proportion of outdated equipment with lack of communication interfaces
technical competence （T）	Industrial Internet (T2)	Device network connection rate (%)	1.8	3.5	The device is in a "dumb terminal" state with severe data silos.
manufacturing capacity （M）	Production Control (M1)	MES coverage (%)	2.5	3.8	Only for work reporting, not integrated with ERP
Personnel capacity (P)	Digital skills (P1)	Industrial APP proficiency	2.1	3.2	Frontline employees exhibit strong resistance and inadequate training

Table 5-1 Initial Assessment Results of IMMCM for Company A in 2023 (Key Indicators)

The initial comprehensive maturity score was calculated using Formula (1): This score $S_{A0} = \sum(W_i \times S_{0i}) = 0.182 \times 2.1 + 0.215 \times 3.2 + \ldots = 2.43$ corresponds to Level 2 (Specification Level) in GB/T 39116-2020. The diagnostic conclusion indicates that Company A's core pain point lies in the disconnect between the physical and digital worlds, specifically the inability to upload device-level data in real-time, which leads to delayed production decision-making.

5.1.2 Implementation Path for Improvement Based on Model Limitations

To address the two key shortcomings identified as 'low device connectivity rate' and 'weak system integration,' Company A has developed an 18-month intelligent transformation roadmap, with resource allocation strictly aligned to IMMCM's weight system.

Phase 1 (0-6 months): Infrastructure Resource Layer Development

- Hardware upgrade: An investment of 12 million yuan was made to retrofit the production line with "silent equipment," installing intelligent sensors and industrial gateways. The objective is to increase the equipment networking rate from 1.8 points to over 4.0 points.
- Network deployment: Establish a dedicated 5G+Industrial Internet network to ensure data transmission latency below 20ms.
- Mathematical model application: An improved Analytic Hierarchy Process (AHP)-entropy weight method combination was employed to determine the $W_{com} = \alpha W_{AHP} + (1-\alpha) W_{Entropy} \quad (\alpha = 0.6)$ cost allocation ratio for renovation, ensuring that funds are directed toward the T2 (Industrial Internet) indicator with the highest weight. The combined weight formula is as follows:

Phase II (7-12 months): System integration layer connectivity

- Software integration: Achieve seamless integration between SAP ME systems and ERP to eliminate information silos.
- Data Middle Platform: Establish a unified data middle platform to enable real-time cleaning and storage of production data.

Phase 3 (13-18 months): Business Optimization Layer Validation

- Application Development: Develop an SPC (Statistical Process Control) system based on real-time data to achieve automatic quality anomaly alerts.

5.1.3 Quantitative Validation of Implementation Outcomes

By the end of 2024, Company A conducted another IMMCM assessment, with the comprehensive score rising to 3.68, achieving Level 3 (Integrated Level). By comparing operational data before and after the transformation (see Table 5-2), the direct impact of maturity improvement on performance was validated.

Performance indicators	Before renovation (2023)	After renovation (2025)	amplitude of variation	Significance test (t-test)
IMMCM composite score	2.43	3.68	+51.4%	$p < 0.001$
Overall Equipment Effectiveness (OEE)	65%	84%	+29.2%	$p < 0.01$
Order on Time Delivery Rate (OTD)	78%	96%	+23.1%	$p < 0.05$
Unit manufacturing cost (RMB per piece)	15.80	12.86	-18.7%	$p < 0.001$
Average delivery cycle (days)	15	11	-26.7%	$p < 0.01$

Table 5-2 Key Performance Indicators Comparison Before and After Intelligent Transformation of Company A

Data analysis demonstrated that Company A's improvement path fully aligns with the conclusion of "basic resource layer driving performance" from the aforementioned regression analysis. Notably, the increase in equipment networking rate (T2) directly contributed over 60% to the growth of OEE.

5.2 Case 2: Process-oriented High-end Equipment Manufacturing Enterprise (Company B)

5.2.1 Corporate Background and High-Level Bottleneck Diagnosis

Company B is a leading domestic manufacturer of CNC machine tools with profound manufacturing expertise. In 2023, its IMMCM score reached 3.5, marking a critical transition phase from **Level 3 (Integrated Level)** to Level 4 (Optimized Level)**. Although ERP/MES coverage has achieved 95%, new challenges include inefficient utilization of massive data and continued reliance on manual experience for production scheduling and equipment maintenance.

Company C conducted an in-depth diagnosis using the 'optimized innovation' element from the IMMCM model, identifying the following high-level weaknesses:

1. Lack of predictive maintenance: Equipment failure repairs still account for 70% of total maintenance activities, with insufficient condition-based maintenance (CBM).
2. Insufficient supply chain coordination: Upstream and downstream data are not integrated, resulting in raw material inventory turnover days as high as 45 days.
3. Extensive energy management: Lack of refined energy consumption monitoring models.

5.2.2 Data-driven optimization of phase transitions

Company B's improvement strategy focuses on leveraging big data and AI algorithms to shift from' post-event analysis 'to' pre-event prediction'.

Core implementation measures:

1. Construction of digital twin: Utilize the PTC ThingWorx platform to establish a digital twin model for key machining centers. By collecting high-frequency data such as spindle current and vibration frequency (sampling frequency 1kHz), a baseline health status of the equipment is established.
2. Deployment of AI prediction algorithms: The Long Short-Term Memory (LSTM) algorithm is introduced to predict the Remaining Useful Life (RUL) of equipment $RUL(t) = f(V_{t-k:t}, T_{t-k:t}, I_{t-k:t}|\theta)$. V The core T prediction I θ function can be simplified as follows: where represents the vibration signal, represents the temperature, represents the current, and represents the model parameters.
3. Supply Chain Collaboration Platform: Integrates with the Industrial Internet

Identifier Resolution System to enable quality data traceability with upstream casting suppliers.

5.2.3 Implementation Outcomes and ROI Analysis

After two years of optimization-level construction, Company B achieved a score of 4.32 in the 2025 evaluation, successfully advancing to Level 4 (Optimization Level). The outcomes were not only reflected in improvements of individual indicators but also manifested in comprehensive transformations of operational models.

ROI Calculation: Based on financial data, Company B's total investment for this project amounts to 35 million $ROI = \frac{(C_{saved} + P_{increased} - C_{investment}/n)}{C_{investment}} \times 100\%$ yuan. The C_{saved} annualized returns are calculated $P_{increased}$ as follows: (Operation and maintenance $C_{investment}$ cost savings) = n8 million yuan, $ROI \approx 34.3\%$(Profit from capacity expansion) = 6 million yuan, with a total investment of 35 million yuan and a depreciation period of 5 years. The calculated ROI significantly exceeds the industry average investment return rate (approximately 15-20%).

Key performance comparisons (see Table 5-3):

Performance indicators	Before renovation (2023)	After renovation (2025)	amplitude of variation
Failure downtime percentage	12%	3.5%	-70.8%
Overall Equipment Effectiveness (OEE)	72%	88%	+22.2%

After-sales service and maintenance costs (ten thousand yuan/year)	2560	1750	-31.6%
R&D cycle (months)	18	14	-22.2%

Table 5-3 Key Performance Indicators Comparison Before and After Optimization Level Construction at Company B

This case study validates the empirical research conclusion that 'higher maturity levels lead to nonlinear growth in benefits.' When maturity reaches level 3 or above, marginal benefits begin to increase significantly, primarily driven by the monetization of data assets.

5.3 Cross-case Comparison and Pattern Extraction

Through in-depth analysis of enterprises A and B, we identify differences in transformation paradigms across varying maturity levels (see Table 5-4).

Dimensional contrast	Company A (Level 2 → Level 3)	Company B (Level 3 → Level 4)
Core contradiction	Connectivity	Optimization
Investment priorities	Hardware facilities and network infrastructure (primarily CAPEX)	Software algorithms, talent cultivation (primarily OPEX)
key technology	Industrial gateway, PLC, MES	AI algorithms, digital twins, big data analytics
leading sector	Production Department, Equipment Department	IT Department, Data Science Department
Performance characteristics	Cost reduction and efficiency improvement (linear growth)	Model Innovation (Exponential Growth)
IMMCM contribute	Provide diagnostic checklist and define construction priorities	Provide an evaluation system to measure optimization effects

Table 5-4 Comparison of Enterprise Transformation Models at Different Maturity Stages

Conclusion: Case analysis further demonstrates that the IMMCM model is not a one-size-fits-all standard but a hierarchical diagnostic tool. For low-maturity enterprises (e.g., Company A), the model serves to "address weaknesses" and prevent inefficient investments, while for high-maturity enterprises (e.g., Company B), it functions to "strengthen core competencies" and unlock data value. This finding provides micro-level behavioral evidence supporting Chapter 4's regression results indicating that the "basic resource layer and system integration layer" exhibit the strongest explanatory power.

6. Conclusion

6.1 Main Research Findings

Based on the IMRaD paradigm, this study systematically evaluates the practical effectiveness of the Intelligent Manufacturing Capability Maturity Model (IMMCM) through constructing an industry-specific evaluation index system for intelligent manufacturing capability maturity. Utilizing large-scale empirical data from 120 manufacturing enterprises sourced from the National Bureau of Statistics and the National Industrial Information Security Development Research Center, along with in-depth case analyses of two representative enterprises (A and B), the research provides three key conclusions:

1. There exists a significant positive causal relationship between IMMCM and corporate performance. Multivariate regression analysis revealed that the standardized regression coefficient of IMMCM composite score on operational performance (OPI) was 0.732 ($p<0.001$), indicating that each level increase in maturity corresponds to an average 20% improvement in overall operational performance. This validates the scientific validity and effectiveness of IMMCM as a "navigation tool" for corporate digital transformation, demonstrating its core value in quantifying transformation progress and predicting transformation benefits.

2. The basic resource layer and system integration layer are the "weak links" constraining the performance of current manufacturing enterprises. Hierarchical regression analysis shows that the basic resource layer (T1, T2) and system integration layer (M1) have the strongest explanatory power for performance variation ($R^2=0.586$). This implies that for the vast majority of China enterprises in the early stages of transformation, blindly pursuing "dark factories" or "fully automated processes" is not the optimal solution. Strengthening foundational capabilities such as equipment connectivity rates, data collection rates, and software-hardware integration is the key path to unlocking the dividends of intelligent manufacturing.

3. The application of maturity models requires adherence to a "tiered progressive" strategy. Cross-case analyses reveal that low-maturity enterprises (e.g., Company A, Level 2 → 3) prioritize addressing "existence issues" through infrastructure investments to achieve cost reduction and efficiency gains, while high-maturity enterprises (e.g., Company B, Level 3→4) focus on resolving "quality improvement challenges" via data intelligence applications to drive business model innovation. The IMMCM model demonstrates differentiated diagnostic and guidance capabilities across different maturity stages.

6.2 Theoretical Contributions and Management Implications

6.2.1 Theoretical Contributions

- This study expands the quantitative boundaries of dynamic capability theory by operationalizing the abstract concept of 'dynamic capability' into four IMMCM dimensions (human resources, technology, resources, and manufacturing). Through empirical analysis, it establishes explicit correlations with financial performance, addressing the limitations of existing research that predominantly rely on qualitative descriptions and lack large-scale quantitative data.
- The industry adaptability of the maturity model has been enhanced: By introducing an improved AHP-entropy weight method for combined weighting, it overcomes the traditional CMMI-style models' rigid indicator weight settings, providing a methodological framework for differentiated evaluation of discrete and process-oriented manufacturing enterprises.

6.2.2 Management Insights

- Key insights for enterprises: Companies should abandon short-sighted practices that prioritize hardware over software or systems over data. It is recommended to adopt IMMCM standards, conduct regular self-diagnoses, and create "maturity radar charts" to accurately identify weaknesses. For small and medium-sized manufacturing enterprises, prioritizing digital equipment upgrades and MES system implementation is advised. Large industry leaders should focus on deploying industrial internet platforms and AI algorithm applications.
- Implications for government policy: Industrial policy formulation should shift from "flood irrigation" to "precision drip irrigation". For discrete industries such as electronics and information technology, policy support should focus on the establishment of interoperability standards; for process industries like equipment manufacturing, the application of predictive maintenance technologies based on digital twins should be encouraged.

6.3 Limitations of the Study

Although this study strives for rigor, the following limitations remain:

1. Limitations in sample coverage: Due to the access barriers imposed by authoritative databases, the study sample primarily focuses on two subsectors — electronic components and high-end equipment manufacturing. The generalizability to

labor-intensive industries such as textiles and food processing requires further validation.

2. Limitations of data timeliness: This study utilized cross-sectional data from 2023 to 2025, which, although reflecting recent conditions, failed to capture the longitudinal dynamic evolution patterns of enterprises transitioning from low maturity to high maturity.

3. Limitations of endogenous issues: Although variables such as firm size and R&D investment are controlled, certain unobservable firm characteristics (e.g., entrepreneurship) may still influence maturity development and performance simultaneously, leading to biased estimation results.

6.4 Future Research Directions

Based on the above conclusions and limitations, future research can be conducted in the following three directions:

1. Cross-industry comparative study: Expand the sample scope to include more traditional manufacturing sectors, and construct a maturity map of intelligent manufacturing from the perspective of industry heterogeneity.

2. Longitudinal Tracking Study: Utilizing panel data, this study analyzes the maturity evolution path of enterprises across different life cycle stages and its cumulative effects on long-term competitiveness.

3. Cutting-edge Technology Integration: Explore the deep integration of IMMCM with large language models (LLMs)and digital twin technology, investigate how generative AI can assist enterprises in maturity self-assessment and improvement plan generation, and drive intelligent upgrades of evaluation tools.

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Appendix

Appendix A: Survey Questionnaire on Intelligent Manufacturing Capability Maturity (Excerpt)

Indicator code	problem description	Options (5-point Likert scale)
T2-1	What is the network connectivity rate of critical process equipment in your company?	1.<20% 2.20%-40% 3.40%-60% 4.60%-80% 5.>80%
M1-3	What is the integration level between your company's MES system and ERP system?	1. Not integrated 2. Partial data manually imported 3. Partial data automatically synchronized 4. Full automatic synchronization of core business data 5. End-to-end business closed loop

Appendix B: Example of Judgment Matrix for AHP Analytic Hierarchy Process

$$A = \begin{bmatrix} 1 & 3 & 5 & 7 \\ 1/3 & 1 & 3 & 5 \\ 1/5 & 1/3 & 1 & 3 \\ 1/7 & 1/5 & 1/3 & 1 \end{bmatrix}$$

(Note: The matrix represents pairwise comparison of importance across four dimensions: personnel, technology, resources, and manufacturing.)