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Research Article

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Influence of intelligent manufacturing on innovation efficiency based on machine learning: A mechanism analysis of government subsidies and intellectual capital

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Abstract: Intelligent manufacturing (IM) is an advanced model that integrates traditional manufacturing with artificial intelligence to achieve automation, intelligence, and flexibility throughout the production process. Chinese enterprises exhibit a relatively low overall innovation efficiency, with a central focus on IM as a powerhouse strategy. The developmental status of IM is pivotal, as it directly affects the quality standards of China's manufacturing industry. This study employed machine learning techniques to examine whether IM can enhance the innovation efficiency of Chinese enterprises while also exploring the roles of government subsidies and intellectual capital in this process. The empirical findings are as follows. (1) Among Chinese listed companies, a higher level of IM significantly improved innovation efficiency, a result confirmed by robustness tests. (2) Mechanism analysis revealed that IM enhanced innovation efficiency primarily by securing government resource support and fostering intellectual capital. (3) Moderation analysis indicated that the positive correlation between IM and innovation efficiency weakened as the level of financial development increased, whereas intensified market competition strengthened this correlation. This study could provide valuable insights for Chinese manufacturing enterprises aiming to enhance their intelligence levels and promote innovation transformation and upgrading.

Keywords: intelligent manufacturing, innovation efficiency, government subsidies, intellectual capital

1 Introduction

In 2015, the State Council of the People's Republic of China issued the "Made in China 2025" notice, outlining a 10-year action program for implementing the manufacturing power strategy in China. China's high-quality development faces both challenges and opportunities. The global manufacturing landscape is rapidly transforming, driven by digitalization, automation, and intelligence. This shift offers China significant opportunities to upgrade its manufacturing sector and strengthen its position in the global value chain. However, China must address challenges such as an aging population, environmental constraints, and the need for innovation-driven growth.

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To achieve high-quality development at this stage, enterprises urgently need to improve the quality and efficiency of their innovation activities through intelligent manufacturing (IM) while simultaneously reducing resource consumption. This practical need underscores the relevance and timeliness of this study.

Given the critical role of IM in advancing China's strategy to become a global manufacturing powerhouse, an increasing number of scholars have begun to examine its impact on corporate behavior. Previous studies have highlighted the positive effects of IM on cost-effectiveness, cost stickiness, operational efficiency, and overall enterprise performance [1–4]. However, they have largely overlooked its influence on corporate innovation. Although Yin and Li [5] explored the relationship between IM and innovation output through quasi-natural experiments based on China's IM pilot project, two key questions remained unanswered.

(1) Does IM truly improve the efficiency of innovation output per unit of R&D investment beyond simply expanding the scale of innovation?
(2) Do the companies selected for IM pilot demonstration projects adequately represent China's broader manufacturing industry?

This study employed machine learning-based text analysis methods to mine IM-related information from the annual reports of manufacturing companies listed on the A-share market in China. In parallel, regression analysis was used to examine whether IM enhances enterprise innovation efficiency, thereby addressing a key gap in existing academic literature.

The operations and activities of enterprises are closely linked to their external environments. When examining the relationship between IM and enterprise innovation efficiency, the impact of external environmental factors is significant. In regions with well-developed financial systems, enterprises face fewer restrictions on financing, which may reduce uncertainties related to intelligent transformation. This facilitates access to the necessary innovation resources, ultimately enhancing enterprise innovation efficiency. Conversely, a well-established financial market can substitute for government resources, thereby reducing the supportive effect of government resources on innovation driven by IM. Intense industry pressures enterprise managers to seek talent and advance their intelligence. Enterprises with advanced intelligence can apply this advantage to improve their innovation efficiency. It is crucial to investigate how financial development and market competition moderate the relationship between IM and enterprise innovation efficiency. This inquiry deepens the understanding of how China's external financing environment and the market competition landscape affect this relationship.

Existing research lacks empirical studies on IM, owing to limited data availability, with most studies remaining theoretical. Empirical research faces challenges in obtaining enterprise data for analysis, particularly when measuring the extent of IM adoption. Consequently, numerous studies have relied on data from the annual list of IM pilot demonstration projects published by the Ministry of Industry and Information Technology for analysis. In this research design, virtual variables were employed to measure the IM of enterprises [2].

This study focused on manufacturing companies listed in the Shanghai and Shenzhen A-share markets in China from 2015 to 2021. This study utilized machine learning technologies for text mining to extract IM-related information from the annual reports of these companies to evaluate their levels of IM.

The selection of listed manufacturing enterprises as research samples was based on several considerations. First, companies listed on A-share markets are subject to strict regulatory standards and disclosure requirements, ensuring the availability and reliability of the financial and operational data required for this study. Second, the Shanghai and Shenzhen Stock Exchanges are the largest and most liquid equity markets in China, offering representative performance and trends within the Chinese manufacturing sector.

When selecting the sample, the study fully considered its representativeness, including companies of various sizes, industries, and regions. However, limiting the sample to manufacturing firms listed on the Shanghai and Shenzhen exchanges introduces certain limitations. This focus may not fully capture the conditions of non-listed manufacturing companies or enterprises listed on Small and medium-sized enterprise (SME) board, growth enterprise market, or other exchanges. Therefore, the findings of this study are primarily applicable to manufacturing firms listed on the Shanghai and Shenzhen stock exchanges, and their applicability to other types of enterprises may be limited.

This study may contribute to innovations in the following areas.

(1) Examining the relationship between IM and enterprise innovation efficiency provides a new perspective in these fields. This exploration helps synthesize successful experiences of intelligent transformation within the manufacturing sector to promote high-quality development. Furthermore, it provides enterprises with decision-making insights to accelerate the transition from traditional kinetic energy to IM.
(2) Methodologically, although existing studies have mostly adopted normative approaches to measure the level of IM in enterprises, this study employed an empirical method. It constructed a word segmentation dictionary and used Python technology to extract textual information from the annual reports of the sample companies to assess the level of IM.
(3) This study integrated resource dependence theory and intellectual capital theory to explain how IM affects enterprise innovation efficiency. The analysis revealed that IM primarily enhanced enterprise innovation efficiency by attracting government subsidies and fostering intellectual capital.
(4) Based on China's external financing and market competition environments, this study explored how financial development and market competition moderate the relationship between IM and innovation efficiency. These findings provide valuable insights for developing intelligence-driven strategies to enhance innovation efficiency in landscapes with varying financing and market competition.

2 Theoretical analysis and research hypothesis

Traditional innovation theories regard the innovation process as an input-output process in which financial and human resources are invested to obtain scientific and technological outputs, often represented by patents. Innovation efficiency reflects the level of output relative to quantitative input in innovation activities. Innovation efficiency can be improved by either reducing innovation input while maintaining or improving output or by obtaining more innovation output with unchanged or reduced input. Scholars argue that differences in internal innovation efficiency among enterprises may result from the allocation of internal innovation resources [6]. Specifically, the low innovation efficiency of enterprises may stem from insufficient financial and human investment in innovation, leading to an inability to carry out innovative projects.

An insufficient investment in innovation funds leads to low innovation efficiency. The highly uncertain innovation process and distorted returns make it difficult for external financiers to evaluate projects, thereby increasing the financing difficulty. Additionally, innovative financing involves information asymmetry, with enterprises often having better project knowledge than financiers do. Reducing information asymmetry through full disclosure is risky because of the potential for external theft [7]. Moreover, the long investment cycle of innovation research and development, coupled with rapidly changing market conditions, increases the possibility of significant valuation errors. These factors cause external financiers to doubt their innovation activities. Therefore, limited funding during innovation restricts the ability to achieve long-term value. However, implementing IM can help enterprises establish stable capital channels, invest in equipment technology, improve internal information communication, and enable innovation [5]. Specifically, digital green value co-creation within business ecosystems enhances resource allocation efficiency and risk-sharing mechanisms, thereby directly improving innovation performance [8]. Qatawneh's research team further observed that artificial intelligence (AI) technology enhanced enterprise R&D investment accuracy by mitigating information asymmetry [9]. In response to China's significant progress in IM, the central government has developed a strategic national framework and implemented relevant policies to promote its widespread adoption [10]. This is consistent with findings from studies on integrated green building supply chains, which highlight the importance of digital integration and green knowledge collaboration in sustaining innovation performance [11]. In the early stages of IM development, government subsidies to enterprises can provide financial security for innovation. These subsidies help mitigate the risks associated with technological innovation, encourage enterprises to pursue independent innovation, and enhance their overall innovation capacity.

Lack of knowledge and talent for innovation can lead to low innovation efficiency. In the innovation process, knowledge is a more crucial resource than traditional resources such as fixed or heavy assets [12].

Marx's statement in "Das Kapital" emphasizes that the difference between economic eras lies in how things are produced and the means of labor used. In the digital economy context, innovation arises from the collision of individual subjective initiatives. As the knowledge economy expands, the importance of intellectual capital increases [13]. Intellectual capital encompasses intangible assets, known as intellectual assets, within an entity. Under certain economic conditions, a company's innovation relies less on tangible assets [14]. In the shift to IM enabled by intellectual capital, traditional manufacturing equipment is upgraded, marketing is more digitally integrated, and product manufacturing modes are reshaped, thereby enhancing enterprise innovation. This study suggests that IM can primarily affect enterprise innovation efficiency through "government resource support" and "driving intellectual capital."

IM enhances enterprise innovation efficiency by providing critical government support. The innovation process is inherently uncertain and poses high risk. When enterprises lack adequate resources for in-depth research, innovation faces significant obstacles [15]. Currently, in China, the market mechanism is imperfect, and the government plays a crucial role in resource allocation, directly affecting enterprise sustainability. Therefore, closer relationships between Chinese enterprises and the government can help secure the resources necessary for innovation [16]. IM aligns with the trends in green transformation and intelligent innovation in the manufacturing sector. This can improve resource utilization efficiency while reducing energy consumption and environmental pollution. Hence, implementing IM is considered an effective strategy for enterprises to establish legitimacy at the government level. This legitimacy facilitates access to critical government resources, such as technical subsidies and tax reduction policies, to lower operating costs and improve operational efficiency [3]. Government-provided innovation subsidies alleviate financial pressure on enterprises, enabling them to allocate more funds to R&D. Scholars have observed that government subsidies can significantly increase the R&D expenditure of enterprises in their core operations [17], indicating that government subsidies for innovation projects can help enterprises allocate internal innovation resources more effectively.

IM enhances innovative ecosystems by driving intellectual capital and improving efficiency. Intellectual capital is defined as all knowledge and capabilities that create value for an organization [18]. Intellectual capital, as a resource for achieving sustainable success, is closely linked to an enterprise's innovation capability [19,20]. In the digital economy, intellectual capital is a strategically significant heterogeneous resource for enterprises. Effectively utilizing intellectual capital can provide enterprises with innovative competitive advantages. IM optimizes the human capital structures of enterprises by attracting high-quality employees to meet the growing demand for knowledge-intensive labor [21]. The arrival of highly educated professionals in enterprises cultivates a culture receptive to new concepts, enriching the organization with high-quality intellectual capital. This infusion of knowledge capital enhances innovation capabilities, as innovation involves the continuous integration and presentation of new ideas. Without knowledge, innovation lacks sources and foundations. IM uses advanced information technology to transcend organizational barriers, integrate cross-organizational information, and serve as a vital knowledge reservoir for enterprise innovation.

3 Research and data methodology

3.1 Sample selection and data sources

This study examined the period from 2015 to 2021. Data were obtained from three databases. (1) The CNRDS database provides the annual number of patents calculated as explained variables and the management and analysis content derived from the annual reports of A-share listed manufacturing companies. (2) The CSMAR database provides research and development costs for the explained variables, the industry Herfindahl index, and corporate governance and financial data for the control variables. (3) The Wind database and the National Bureau of Statistics provide the balance of deposits and loans of provincial financial institutions and the provincial GDP data required to calculate the financial development level index.

The data were screened using the following criteria: (1) samples with missing data for key variables were omitted; (2) companies listed on the B-share or H-share markets were excluded; and (3) samples with asset-liability ratios exceeding 1 were omitted. After applying these criteria, the study retained 10,882 sample observations covering 2,450 listed manufacturing companies. Continuous variables were winsorized at the 1 and 99% percentiles to address outliers.

3.2 Model setting

According to the study by Yang et al. [22], a regression model can be constructed to assess the impact of the influencing variables on enterprise innovation efficiency. The process of setting up a regression model involved three steps.

Step 1: Define the dependent variable.

Step 2: Identify the explanatory variables.

Step 3: Select an appropriate regression model based on the characteristics of the main variables and probability distribution of their error terms.

Based on the above analysis, this study outlined the impact pathway of IM on innovation efficiency, as illustrated in Figure 1, and proposed the following hypothesis:

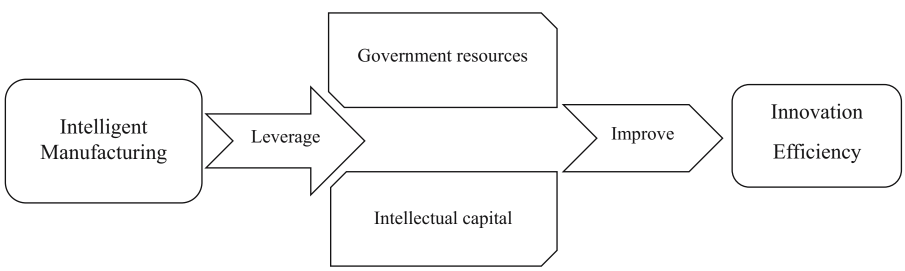

Figure 1: Impact pathway of IM on enterprise innovation efficiency. Source: Created by the authors.

H1: Enterprises implementing IM can improve innovation efficiency.

The measurement model used in this study is as follows:

$$\begin{aligned}\mathrm{IE}_{i,t} = {} & \beta_0 + \beta_1\mathrm{IM}_{i,t} + \beta_2\mathrm{Size}_{i,t} + \beta_3\mathrm{Age}_{i,t} + \beta_4\mathrm{TQ}_{i,t} + \beta_5\mathrm{Lev}_{i,t} + \beta_6\mathrm{Roa}_{i,t} + \beta_7\mathrm{Salary}_{i,t} + \beta_8\mathrm{Cash}_{i,t} + \beta_9\mathrm{SOE}_{i,t} \\ & + \delta_\mathrm{p} + \mu_t + \varphi_\mathrm{q} + \varepsilon_{i,t},\end{aligned} \tag{1}$$

where subscript i represents the listed manufacturing company; subscript t represents the year; IE represents the innovation efficiency of the enterprise; IM represents intelligent manufacturing; and the coefficient terms β_2–β_9 denote a series of control variables. In addition, province (δ_p), year (μ_t), and industry (φ_q) fixed effects are also controlled. As innovation efficiency is a limited variable, the Tobit model was used for the regression analysis. To ensure robust significance of the panel regression results, the reported t-statistics were adjusted by default using robust standard errors for clustering at the firm level. The secondary manufacturing industry of the CSRC industry standard was classified based on the China Statistical Yearbook following existing research practices [5].

3.3 Variable definition

(1) Explained variables: Innovation efficiency (IE). Some scholars define IE as the ability of a company's R&D investment to generate patents and patent citations [23]. This study described IE as the ratio of actual

innovation output to input factors. Innovation output was measured by the number of patent applications and innovation input was measured by R&D expenditure. To account for the lag in innovation output, the number of patent applications in the next period was used in the calculation process.

$$\mathrm{IE}_t = \frac{\mathrm{Ln}(\mathrm{Patent}_{t+1} + 1)}{\mathrm{Ln}(\mathrm{R\&D\ expenditure}_t)}. \tag{2}$$

(2) Explanatory variables: IM. This study applied existing research and annual report data to assess the level of enterprise intelligence transformation.

This study integrated a dictionary-based text mining approach with natural language processing tools to extract keywords related to IM from corporate annual reports. This process enables the assessment of IM levels by establishing a structured feature dictionary that includes IM information [5], as outlined in Table 1. We employed Python's Jieba library to perform Chinese word segmentation of the report texts. Jieba supports custom dictionaries that effectively identify technical terms while reducing segmentation errors.

Table 1: Summary of structured feature words of IM

Index	Measurement dimension	Keywords
IM	AI technology	AI, IM, wisdom manufacturing, active manufacturing, intelligent transformation, business intelligence, image understanding, intelligent data analysis, intelligent robots, manufacturing execution systems, smart manufacturing, machine learning, deep learning, integration, unmanned, human-computer interaction, bioidentification technology, face recognition, intelligent terminal, voice recognition
	Internet technology	Industrial Internet, mobile Internet, e-commerce, mobile payment, cloud computing, exascale concurrency, Internet of Things, information physical system, cyber physical system, EB-level storage, cloud manufacturing
	Big data technology	Big data, data mining, data visualization, virtual reality, industrial digitization, data-driven, heterogeneous data, data twin, text mining, mixed reality
	Value chain intelligent manufacturing technology	Planning and scheduling, production execution, equipment operation and maintenance, intelligent warehousing, intelligent distribution, network collaboration, intelligent marketing, intelligent customer service, intelligent home, intelligent wear, intelligent agriculture, intelligent medicine

Compared with other IM evaluation index systems, the method used in this study offers several advantages. (1) Comprehensiveness: The multi-dimensional feature dictionary more thoroughly captures all aspects of IM. (2) Dynamism: The construction process allows rapid updates to reflect technological advancements, ensuring the timeliness of research. (3) Practicality: Relevant IM information can be effectively extracted from large volumes of unstructured data using text mining technology.

However, this method has certain limitations. (1) Data dependency: The accuracy of results is highly dependent on the quality and completeness of the keyword dictionary. (2) Technological limitations: Despite efforts to ensure the comprehensiveness of the dictionary, some emerging technologies or terms may not be captured. (3) Interpretability: Text mining may not fully explain the deeper logic and complex relationships underlying IM.

Keyword selection is crucial for accurately measuring IM. This study primarily selected keywords related to IM from academic research and relevant policy documents. For academic research, works by Wen et al. [3] and Wu et al. [24] were referenced to preliminarily identify keywords related to AI technology, Internet technology, big data, and value chain-oriented IM technologies. To enhance the feature lexicon, key policy documents such as the Made in China 2025 IM Development Plan (2016–2020) and the Government Work Report were used as foundational frameworks, further supplementing terms related to the aforementioned technologies.

To minimize irrelevant noise from the frequency of search words in the annual report, such as when key phrases appear in sections such as shareholders or creditors, this study restricted the search scope to the management analysis and discussion sections. To account for variations in the length of the MD&A sections in annual reports across listed companies, this study calculated the proportion of keyword combinations to the total number of words. The calculation process is as follows:

$$\mathrm{IM}_{i,t} = \frac{\sum \text{Keyword frequency}_{i,t}}{\text{Total number of words}_{i,t}} \times 100. \tag{3}$$

(3) Control variables and moderating variables. The control variables in this study were based on existing research and mainly controlled for key factors influencing technological innovation in Chinese enterprises [25]. These included company size, establishment period, Tobin's Q value, asset-liability ratio, return on total assets, executive compensation, cash ratio, and ownership nature. The moderating variables were the levels of financial development and industry competition. Financial development was measured using the ratio of deposit and loan balances to the GDP of financial institutions in each province, and industry competition was indicated using the Herfindahl index. The definitions of these variables are presented in Table 2.

Table 2: Main variable definitions of IE and IM

Variable class	Variable name	Variable abbreviation	Variable instructions
Explained variable	Innovation efficiency	IE	The calculation formula is given above
Explanatory variable	Intelligent manufacturing	IM	The calculation formula is given above
Control variables	Company size	Size	Size = Ln (Total assets)
	Establishment period	Age	Age = Ln (Years of establishment)
	Tobin's Q value	TQ	TQ = Firm market value/Firm replacement cost
	Asset-liability ratio	Lev	Lev = Total liabilities/Total assets
	Return on total assets	Roa	Roa = Net profit/Average total assets
	Executive compensation	Salary	Salary = Ln (Total compensation of top three executives)
	Cash ratio	Cash	Cash = Cash balance/Total assets
	Ownership nature	SOE	If the actual controller of the company is state-owned, it is assigned a value of 1, otherwise it is assigned a value of 0
Moderating variables	Financial development level	FE	FE = Province deposit and loan balance /GDP
	Degree of industry competition	HHI	$\mathrm{HHI} = \sum\left(\frac{X_i}{X}\right)^2$, where $X = \sum X_i$, X_i is the main business income in the industry

4 Empirical results and analysis

4.1 Descriptive statistics

Table 3 presents descriptive statistics for the key variables in this study. The data showed that the minimum IE among the sample companies was 0, the maximum was 0.3394, and the average was 0.1825. This suggests a generally low level of IE among the listed manufacturing enterprises in China. The minimum value of IM among the sample companies was 0, indicating that some firms did not disclose information about intelligent transformation in their annual reports. Conversely, the maximum value was 3.0382, with an average of 0.3084, indicating significant variation in the extent of intelligent transformation among listed manufacturing enterprises in China.

Table 3: Descriptive statistics of main variables

Variable name	Observation	Mean value	Standard deviation	Minimum	Median	Maximum
IE	10,882	0.1825	0.0781	0.0000	0.1927	0.3394
IM	10,882	0.3084	0.5081	0.0000	0.1239	3.0382
Size	10,882	21.9678	1.0635	20.0498	21.8533	24.9849
Age	10,882	2.8487	0.3113	1.0986	2.8904	4.1271
TQ	10,882	2.1614	1.3037	0.8841	1.7405	8.4065
Lev	10,882	0.3750	0.1841	0.0573	0.3620	0.8404
Roa	10,882	0.0476	0.0691	−0.2496	0.0460	0.2279
Salary	10,882	14.4910	0.6327	13.0388	14.4643	16.2393
Cash	10,882	0.1526	0.1151	0.0116	0.1208	0.5755
SOE	10,882	0.2094	0.4069	0.0000	0.0000	1.0000
FE	10,882	3.7385	1.3168	2.0628	3.5383	8.1310
HHI	10,882	0.1112	0.0942	0.0282	0.0871	1.0000

4.2 Baseline regression results

The explained variable in this study, IE, was calculated as the ratio of the number of patent applications to R&D expenditure. Because the number of patent applications follows a Poisson distribution and cannot be less than 0, even when transformed logarithmically, the ordinary least squares (OLS) method cannot be adopted to estimate the transformed data to obtain a consistent estimator [26]. Given this characteristic, this study used the Tobit model for the regression analysis.

The Tobit model is specifically designed to address truncated data, as is the case in this study, where IE cannot fall below 0. This distribution feature renders traditional linear regression models unsuitable because they cannot adequately account for the constraints of restricted data. Compared with other models that handle restricted data, such as two-point estimation methods or truncated regression models, the Tobit model provides greater flexibility for continuously distributed dependent variables. Therefore, considering the nature of the IE variable and the advantages of the Tobit model in managing restricted dependent variables, we selected the Tobit model for regression analysis to ensure the accuracy and reliability of our research results.

Table 4 presents the Tobit model estimation results for the explained variables, where columns (1)–(3) indicate a significant positive correlation between IM and IE at the 1% significance level. This suggests that promoting intelligent transformation in manufacturing enterprises significantly enhances the input-output ratio of internal innovation activities, confirming H1. These findings suggest that implementing IM not only benefited from government resource support but also promoted the introduction of high-level talent and knowledge in patent R&D. This helped enterprises innovate, upgrade, and contribute to the high-quality development of China’s manufacturing sector.

Notably, the research sample consisted solely of listed companies, excluding non-listed companies. Compared with their non-listed counterparts, listed companies typically operate on a larger scale, have more abundant financial resources, exhibit higher levels of intelligent transformation, and enjoy greater access to government support and intellectual capital. Theoretically, these advantages may lead to a more pronounced impact on IE. Although controlling for variables such as company size and ownership can partially mitigate heterogeneity, our findings are more applicable to listed companies. Further research is required to examine non-listed firms. Future studies could expand the sample by incorporating data from the New Third Board and regional equity markets.

4.3 Robustness test

(1) Instrumental variable regression. To strengthen causal inference regarding the impact of IM on enterprise IE, this study investigated endogenous issues. Considering a potential scenario in which enterprises with

Table 4: Influence of IM on enterprise IE

Variable name	(1) IE	(2) IE	(3) IE
IM	0.0318***	0.0280***	0.0253***
	(14.0335)	(14.8286)	(12.9189)
Size		0.0188***	0.0216***
		(12.2250)	(14.0522)
Age		−0.0204***	−0.0160***
		(−5.0258)	(−3.8622)
TQ		−0.0038***	−0.0018*
		(−4.2321)	(−1.8490)
lev		0.0363***	0.0319***
		(4.1309)	(3.7365)
Roa		0.1102***	0.1095***
		(6.1213)	(6.4302)
Salary		0.0105***	0.0087***
		(4.9630)	(3.8406)
Cash		−0.0037	0.0098
		(−0.3745)	(1.0187)
SOE		0.0087***	0.0092***
		(2.6130)	(2.8338)
Year			Controlled
Province			Controlled
Industry			Controlled
Constant	0.1711***	−0.3471***	−0.4073***
	(101.4897)	(−9.7157)	(−11.1254)
Observation	10,882	10,882	10,882
Pseudo R^2	−0.0210	−0.0999	−0.1601
F value	196.94	93.50	66.02

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, and the *t* values adjusted by clustered standard errors are in parentheses.

higher IE are more likely to engage in intelligent transformation, it is crucial to address the possibility of reverse causality between IM implementation and enterprise innovation. This study used the IV Tobit model to control for causal endogeneity.

Building on research by scholars on productivity enhancement through Internet technology [27], this study used a cross-term variable. It consists of the lagged number of Internet users in China and the number of fixed telephones per 10,000 individuals in each prefecture-level city in 1984. This variable served as the primary instrumental variable (IV_1) for assessing the current level of IM. Given that an enterprise's decision to adopt smart manufacturing can be influenced by the historical infrastructure construction in its region, this instrumental variable meets the relevance requirement. Theoretically, the IV satisfies the externality requirement. Telecommunications and information transmission services can primarily offer communication services to residents in a region without directly correlating with the innovation activities of enterprises and their efficiency. Furthermore, following the methodology proposed by Wen et al. [3], this study used the current level of IM as an instrumental variable (IV_2) lagged by one phase. Column (1) of Table 5 presents the first-stage regression results for the IV Tobit model. The regression coefficients of IV_1 and IV_2 were significantly positive at the 10 and 1% levels, respectively, indicating a correlation between the instrumental variables. Column (2) in Table 5 shows the regression results of the second stage, revealing a significant Chi-square value in the Wald exogeneity test at the 1% level, indicating exogeneity of the instrumental variable. Importantly, the regression coefficient of instrumental variable IM was significantly positive at the 1% level, which is consistent with the primary analysis.

Table 5: Robustness test of intelligent manufacturing on enterprise IE: endogenous problem

Variable name	(1) IM	(2) IE
IM		0.0294***
		(11.6361)
IV_1	0.0109*	
	(1.9196)	
IV_2	0.7932***	
	(63.2862)	
Control variables	Controlled	Controlled
Year	Controlled	Controlled
Province	Controlled	Controlled
Industry	Controlled	Controlled
Constant	0.1510	−0.3970***
	(1.1889)	(−9.9935)
Observation	7,976	7,976
R^2/Pseudo R^2	0.6914	
F value/Chi square value	131.54	2312.41
Wald test value		41.27***

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, and the t values adjusted by clustered standard errors are in parentheses.

(2) Replacing the explained variables. To address the potential confounding effects arising from the measurement methodology of IE, this study adopted a recalibrated approach based on prior research [28]. The revised formula for IE is as follows:

$$\mathrm{IE}_t = \mathrm{Ln}\left[\frac{\mathrm{Patent}_t}{(\text{R\&D expenditure}_{t-1} + \text{R\&D expenditure}_{t-2})/\mathrm{Asset}_t} + 1\right]. \tag{4}$$

The test outcomes are presented in column (1) of Table 6. The regression coefficient of IM was significant at the 1% level and aligned with the primary analysis.

Table 6: Robustness test of IM on enterprise IE: variable selection and model setting

Variable name	(1) IE	(2) IE	(3) IE	(4) IE
IM	0.4040***	0.0258***	0.0136***	0.0133***
	(9.2296)	(12.3896)	(6.8301)	(6.8546)
Control Variables	Controlled	Controlled	Controlled	Controlled
Year	Controlled	Controlled	Controlled	Controlled
Province	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled
Constant	−13.0843***	−0.3935***	−0.5402***	−0.0888
	(−14.9325)	(−9.4205)	(−15.2196)	(−1.2779)
Observation	10,590	8,389	10,882	10,882
R^2/Pseudo R^2	0.0734	−0.1625	−0.2232	0.3507
F value	40.34	58.83	54.44	59.84

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, and the t values adjusted by clustered standard errors are in parentheses.

Furthermore, some scholars suggest that certain innovation outputs may span more than 1 year [29]. Therefore, the formula for calculating IE was adjusted to

$$\mathrm{IE}_t = \frac{\mathrm{Ln}(\mathrm{Patent}_{t+2} + 1)}{\mathrm{Ln}(\text{R\&D expenditure}_t)}. \tag{5}$$

The regression results are shown in column (2) of Table 6. The regression coefficient of IM was positive at the 1% significance level, consistent with the main test.

(3) Model setting problem. To mitigate potential industry-specific effects, this study initially categorized the sample companies according to the 2012 standard set by the China Securities Regulatory Commission. The regression results after industry reclassification are shown in column (3) of Table 6, where the regression coefficient of IM was significant at the 1% level, consistent with the primary analysis. Subsequently, OLS regression was used to re-estimate the dependent variables, and the results are displayed in column (4) of Table 6. Again, the regression coefficient of IM was significant at the 1% level, confirming the primary analysis.

This study attempted to minimize omitted variable bias by incorporating multi-dimensional control variables and applying robust statistical methods. However, certain limitations remain. Future research should explore the influence of additional factors not captured by the current model, potentially through more refined text mining and multi-source data fusion.

5 Further analysis

5.1 Mediating effect test

This study used a three-step method of testing the mediating effects to systematically examine the mediating effects of pathways involving “government resource support” and “driving intellectual capital” [30]. First, IM was regressed against enterprise IE, and further analysis may proceed if the coefficient was significant. Second, IM was regressed against the mediator. In the third step, the mediator was included, and IM and enterprise IE underwent the regression again. If the mediator coefficient is significant and there is a decrease in the absolute value of the effect coefficient of IM on enterprise IE while remaining significant, this suggests partial mediation of the influence of IM on enterprise IE.

Government resource support was primarily measured through government subsidies and was divided into three categories:

Total government subsidy (Sub_Tot): Measured as the total amount of government subsidies received by a company on an annual basis.

Innovative government subsidies (Sub_Inn): Measured as subsidy projects directly related to innovation, identified through text analysis of the “government subsidy details” in the annual reports of enterprises. This includes keywords such as “innovation,” “research and development,” “patents,” and “technological breakthroughs.”

Non-innovative government subsidies (Sub-Non): Measured as the total subsidies minus innovation-related subsidies. This category includes support such as environmental and employment subsidies.

Intellectual capital is measured by the education level of an enterprise’s workforce, using the following indicators:

Proportion of employees with a bachelor’s degree or higher (Edu_1): The proportion of employees in a company who hold a bachelor’s degree or higher.

Proportion of employees with a master’s degree or higher (Edu_2): The proportion of employees in a company who hold a master’s degree or higher.

(1) Mediating effect of government subsidies. IM enhanced enterprise IE by leveraging government resource support. This support was mainly provided through financial subsidies and other means to address insufficient investments in enterprise innovation funds. Therefore, total government subsidy (Sub_Tot) was selected as the proxy variable for government resource support. Simultaneously, certain studies have indicated that innovation and “innovation government subsidies” and “non-innovation government subsidies” have varying policy effects on the innovation output and input of enterprises [31]. To assess whether these policy effects can affect IE, this study included innovative government subsidies (Sub_Inn) and non-innovative government subsidies (Sub_Non) as mediating variables. The data collection for these subsidies followed previous studies that used the text analysis method to conduct keyword searches on detailed subsidy items. This approach can help identify items belonging to innovative and non-innovative government subsidies, with

the number of subsidies summarized by different items [31,32]. The regression model for testing the intermediary effect of government subsidies in the first step was the same as in benchmark regression model (1), with the regression model settings for the second and third steps shown in (6) and (7).

$$\mathrm{Sub}_{\mathrm{Tot}i,t}\left(\frac{\mathrm{Sub}_{\mathrm{Inn}i,t}}{\mathrm{Sub}_{\mathrm{Non}i,t}}\right) = \beta_0 + \beta_1\mathrm{IM}_{i,t} + \beta_2\mathrm{Size}_{i,t} + \beta_3\mathrm{Age}_{i,t} + \beta_4\mathrm{TQ}_{i,t} + \beta_5\mathrm{Lev}_{i,t} + \beta_6\mathrm{Roa}_{i,t} + \beta_7\mathrm{Salary}_{i,t} + \beta_8\mathrm{Cash}_{i,t} + \beta_9\mathrm{SOE}_{i,t} + \delta_{\mathrm{p}} + \mu_t + \varphi_{\mathrm{q}} + \varepsilon_{i,t}, \tag{6}$$

$$\mathrm{IE}_{i,t} = \beta_0 + \beta_1\mathrm{IM}_{i,t} + \beta_2\mathrm{Sub}_{\mathrm{Tot}i,t}\left(\frac{\mathrm{Sub}_{\mathrm{Inn}i,t}}{\mathrm{Sub}_{\mathrm{Non}i,t}}\right) + \beta_3\mathrm{Size}_{i,t} + \beta_4\mathrm{Age}_{i,t} + \beta_5\mathrm{TQ}_{i,t} + \beta_6\mathrm{Lev}_{i,t} + \beta_7\mathrm{Roa}_{i,t} + \beta_8\mathrm{Salary}_{i,t} + \beta_9\mathrm{Cash}_{i,t} + \beta_{10}\mathrm{SOE}_{i,t} + \delta_{\mathrm{p}} + \mu_t + \varphi_{\mathrm{q}} + \varepsilon_{i,t}. \tag{7}$$

The regression results for the initial step of the mediating effect test are presented in column (3) of Table 4, showing a significantly positive coefficient for the influence of IM on enterprise IE. In the second step, as indicated in columns (1), (3), and (5) of Table 7, the coefficients of IM were all positively significant at the 1% level, indicating a significant increase in Sub_Tot, Sub_Inn, and Sub_Non because of IM. In the third step, as shown in columns (2), (4), and (6) of Table 7, the coefficients for Sub_Tot, Sub_Inn, and Sub_Non are all significantly positive, suggesting that regardless of subsidy type, it contributed significantly to enhance enterprise IE. Interestingly, compared to the coefficients in column (3) of Table 4, the absolute values of the IM coefficients in columns (2), (4), and (6) of Table 7 decreased, indicating partial mediation of the positive impact of IM on enterprise IE by government subsidies.

Table 7: Mechanism test of IM affecting enterprise IE: government subsidies

Variable name	(1) Sub_Tot	(2) IE	(3) Sub_Inn	(4) IE	(5) Sub_Non	(6) IE
IM	0.2963***	0.0216***	0.0223***	0.0247***	0.1751***	0.0234***
	(10.4558)	(11.4312)	(3.6655)	(12.7584)	(7.6179)	(12.0140)
Sub_Tot		0.0125***				
		(11.4825)				
Sub_Inn				0.0290***		
				(6.4345)		
Sub_Non						0.0111***
						(7.0087)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Province	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	−3.0484***	−0.3689***	0.4905***	−0.4215***	1.4983***	−0.4237***
	(−6.0922)	(−10.3047)	(6.6061)	(−11.5645)	(4.6701)	(−11.7004)
Observation	10,882	10,882	10,882	10,882	10,882	10,882
R^2/Pseudo R^2	0.5006	−0.1754	0.1019	−0.1630	0.0961	−0.1650
F value	113.67	71.86	15.44	66.20	14.06	67.64

Note: ***, **, and * in the table indicate significance levels of 1%, 5%, and 10%, respectively, and the *t* values adjusted by clustering standard error are in parentheses.

(2) This study examined the mediation effect of intellectual capital, building on the analysis indicating that IM drives enterprises' intellectual capital, which in turn stimulates internal innovation and enhances IE. Intellectual capital comprising human capital and knowledge was evaluated using the framework proposed by Lu and Huang [33]. Employee education level was selected as the mediating variable, measured by the proportion of individuals holding bachelor's degrees or higher (Edu_1) and master's degrees or higher (Edu_2) in the total workforce. To address the missing data in Edu_1 and Edu_2, observations with void values for these variables were omitted, resulting in a sample size of 7,093. The regression model for the first step of the

intellectual capital mediating effect test mirrored benchmark regression model (1), while the regression model specifications for the second and third steps are presented in equations (8) and (9).

$$\begin{aligned}\mathrm{Edu\_1}_{i,t}(\mathrm{Edu\_2}_{i,t}) = {} & \beta_0 + \beta_1\mathrm{IM}_{i,t} + \beta_2\mathrm{Size}_{i,t} + \beta_3\mathrm{Age}_{i,t} + \beta_4\mathrm{TQ}_{i,t} + \beta_5\mathrm{Lev}_{i,t} + \beta_6\mathrm{Roa}_{i,t} + \beta_7\mathrm{Salary}_{i,t} \\ & + \beta_8\mathrm{Cash}_{i,t} + \beta_9\mathrm{SOE}_{i,t} + \delta_\mathrm{p} + \mu_t + \varphi_\mathrm{q} + \varepsilon_{i,t},\end{aligned} \tag{8}$$

$$\begin{aligned}\mathrm{IE}_{i,t} = {} & \beta_0 + \beta_1\mathrm{IM}_{i,t} + \beta_2\mathrm{Edu}_{1i,t}(\mathrm{Edu}_{2i,t}) + \beta_3\mathrm{Size}_{i,t} + \beta_4\mathrm{Age}_{i,t} + \beta_5\mathrm{TQ}_{i,t} + \beta_6\mathrm{Lev}_{i,t} + \beta_7\mathrm{Roa}_{i,t} + \beta_8\mathrm{Salary}_{i,t} \\ & + \beta_9\mathrm{Cash}_{i,t} + \beta_{10}\mathrm{SOE}_{i,t} + \delta_\mathrm{p} + \mu_t + \varphi_\mathrm{q} + \varepsilon_{i,t}.\end{aligned} \tag{9}$$

Table 8 presents the results of the mediating effect test for intellectual capital. In the first step, the regression results in column (1) demonstrated a significantly positive coefficient for the impact of IM on enterprise IE at the 1% level. In the second step, as indicated in columns (2) and (4) of Table 8, the coefficients of IM were both positively significant at the 1% level, suggesting that IM significantly enhanced intellectual capital. In the third step, as shown in columns (3) and (5) of Table 8, the coefficients of Edu_1 and Edu_2 were significantly positive at the 10 and 5% levels, respectively, indicating that IM effectively attracted high-quality employees, thereby enhancing enterprise IE. Interestingly, compared with column (1), the absolute values of the IM coefficients in columns (3) and (5) of Table 8 decreased, suggesting partial mediation of the positive impact of IM on enterprise IE by intellectual capital.

Table 8: Mechanism test of IM affecting enterprise IE: intellectual capital

Variable name	(1) IE	(2) Edu_1	(3) IE	(4) Edu_2	(5) IE
IM	0.0248***	0.0674***	0.0236***	0.0148***	0.0240***
	(10.9247)	(8.7549)	(9.9791)	(5.9949)	(10.4931)
Edu_1			0.0176*		
			(1.8563)		
Edu_2					0.0582**
					(2.0922)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled
Year	Controlled	Controlled	Controlled	Controlled	Controlled
Province	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	−0.4062***	−0.2032*	−0.4026***	−0.1526***	−0.3973***
	(−9.5145)	(−1.9572)	(−9.4146)	(−4.7769)	(−9.2903)
Observation	7,093	7,093	7,093	7,093	7,093
R^2/Pseudo R^2	−0.1703	0.2799	−0.1710	0.2808	−0.1710
F value	48.54	17.00	48.17	10.40	47.87

Note: ***, **, and * in the table indicate significance levels of 1%, 5%, and 10%, respectively, and the *t* values adjusted by clustering standard error are in parentheses.

5.2 Moderating effect test

(1) Moderating role of financial development. The external financing environment can significantly affect the technological innovation efforts of enterprises, as substantial financial support is crucial for R&D initiatives. However, owing to the confidential and specialized nature of R&D activities, financial institutions may face challenges in fully understanding the R&D landscapes of enterprises, leading to significant information asymmetry. The information gap constrains innovation by limiting external financing. An efficient financial market can help alleviate financing difficulties for enterprises by spreading R&D risks, efficiently allocating financial resources, and reducing information asymmetry, thereby promoting technological innovation [34]. As noted earlier, IM can enhance enterprise innovation by accessing government resources, particularly financial subsidies. A similar effect can be observed in developed financial markets. Thus, a higher level of financial development can substitute for the government's resource-support effect on intelligent transformation. In

developed financial markets, the market, often described as the "invisible hand," replaces the government, acting as the "visible hand," in facilitating the resource allocation. Building on these theoretical foundations, this study explored the moderating influence of financial development on the relationship between IM and IE. To achieve this, this study included the financial development level (FE) and the interaction term (IM × FE) between IM and financial development level in Model (10) for empirical validation.

$$\begin{aligned}\mathrm{IE}_{i,t} = {} & \beta_0 + \beta_1\mathrm{IM}_{i,t} + \beta_2\mathrm{IM}_{i,t} \times FE_{i,t} + \beta_3 FE_{i,t} + \beta_4\mathrm{Size}_{i,t} + \beta_5\mathrm{Age}_{i,t} + \beta_6\mathrm{TQ}_{i,t} + \beta_7\mathrm{Lev}_{i,t} + \beta_8\mathrm{Roa}_{i,t} \\ & + \beta_9\mathrm{Salary}_{i,t} + \beta_{10}\mathrm{Cash}_{i,t} + \beta_{11}\mathrm{SOE}_{i,t} + \delta_{\mathrm{p}} + \mu_t + \varphi_{\mathrm{q}} + \varepsilon_{i,t}.\end{aligned} \tag{10}$$

Column (1) of Table 9 displays the regression results after including the cross-product term of IM and level of financial development. In column (1), the regression coefficient of the cross-product term IM×FE was negative and significant at the 1% level. This finding indicated that a higher level of financial development attenuated the positive impact of IM on enterprise IE.

Table 9: Test of the regulatory effect of IM on enterprise IE

Variable name	**(1) IE**	**(2) IE**
IM	0.0369***	0.0303***
	(8.7627)	(10.2542)
IM × FE	−0.0026***	
	(−3.0784)	
FE	0.0063**	
	(2.1874)	
IM × HHI		−0.0413**
		(−2.0407)
HHI		0.0735***
		(4.9651)
Control variables	Controlled	Controlled
Year	Controlled	Controlled
Province	Controlled	Controlled
Industry	Controlled	Controlled
Constant	−0.4414***	−0.4220***
	(−11.2400)	(−11.5602)
Observation	10,882	10,882
Pseudo R^2	−0.1610	−0.1641
F value	63.96	64.10

Note: ***, **, and * in the table indicate significance levels of 1%, 5%, and 10%, respectively, and the *t* values adjusted by clustering standard error are in parentheses. The same below.

In regions with lower levels of financial development, external financing channels for enterprises are limited, making government subsidies a crucial resource for bridging the gap in innovation funding. In contrast, enterprises in regions with more advanced financial systems can access funds through market-oriented mechanisms, such as bank loans and equity financing, thereby reducing their reliance on government support. Consequently, the marginal utility of government subsidies diminishes, weakening the innovation-enhancing effect of IM.

This suggests that, in the Chinese context, some enterprises may misallocate or inefficiently use financial resources. The financial market exhibits short-term orientation and prioritizes low-risk projects with quick returns. In contrast, IM innovation is characterized by long-term horizons and high uncertainty, which can cause funds to divert toward non-innovative fields. As a result, market-based financing often fails to identify high-potential innovation projects, particularly in fields with significant information asymmetry such as core AI technologies, resulting in inefficient use of financial resources.

In the long run, financial development can eliminate inefficient enterprises through competitive mechanisms, thereby optimizing resource allocation. The current negative regulatory effects may reflect the growing pain caused by China's economic transition. However, it is essential to align financial resources efficiently with IM innovation. This can be achieved by strengthening institutional innovation and advancing technological and financial tools.

(2) Moderating effect of industry competition. In highly competitive industries, enterprises face increased market pressure, motivating them to utilize IM technologies to maintain or improve their competitive edge. Therefore, the positive impact of IM on enterprise innovation may be more pronounced in industries with higher competition levels [5]. Concurrently, highly competitive product markets facilitate mitigation of corporate agency conflicts. This encourages enterprises to invest cash in innovation projects that enhance corporate value [35]. Building on these theories, this study examined the moderating effect of industry competition on the relationship between IM and IE. It incorporated the industry competition level (HHI) and another interaction term (IM×HHI) between IM and industry competition into model (11) for validation.

$$\begin{aligned}\mathrm{IE}_{i,t} = {} & \beta_0 + \beta_1\mathrm{IM}_{i,t} + \beta_2\mathrm{IM}_{i,t} \times \mathrm{HHI}_{i,t} + \beta_3\mathrm{HHI}_{i,t} + \beta_4\mathrm{Size}_{i,t} + \beta_5\mathrm{Age}_{i,t} + \beta_6\mathrm{TQ}_{i,t} + \beta_7\mathrm{Lev}_{i,t} + \beta_8\mathrm{Roa}_{i,t} \\ & + \beta_9\mathrm{Salary}_{i,t} + \beta_{10}\mathrm{Cash}_{i,t} + \beta_{11}\mathrm{SOE}_{i,t} + \delta_\mathrm{p} + \mu_t + \varphi_\mathrm{q} + \varepsilon_{i,t}.\end{aligned} \tag{11}$$

In this study, the Herfindahl–Hirschman Index was used to measure industry competition levels. A higher HHI indicates greater market concentration and reduced competition, whereas a lower HHI indicates increased competition. The regression results in column (2) of Table 9 indicated that the coefficient of the cross-product term IM×HHI was significantly negative at the 5% level. This finding suggests that increased industrial competition strengthens the positive relationship between IM and enterprises' IE.

Additional findings (Table not shown) reveal that the research conclusions vary across sectors of the manufacturing industry. The positive impact of IM on IE is most evident in light industry. For example, Ma'ruf et al. [36] highlighted that in customized manufacturing, intelligent technologies play a significant role in transforming traditional production models through data-driven decision optimization.

6 Discussion, conclusion, and implications

6.1 Discussion

Although Yin and Li [5] examined IM's effects on innovation output, this study advances the discourse by conceptualizing innovation as the efficiency ratio of output to input, offering a more nuanced understanding of how IM enhances resource utilization. These findings are consistent with both resource dependence theory and intellectual capital theory, highlighting the interplay between external resource acquisition and internal knowledge accumulation, an integrated perspective rarely addressed in earlier works [14,20].

Although this study offers valuable insights, its focus on listed manufacturing firms limits the generalizability of the findings to SMEs and non-listed enterprises, which often face different resource constraints. Additionally, although the text mining approach is innovative, it relies on predefined dictionaries that may not fully capture rapidly evolving IM terminologies.

This study also highlights several promising avenues for future research that could deepen our understanding of and engagement with transformative technologies. Potential directions include:

(1) Investigating the impact of IM on a broader set of corporate performance indicators such as production efficiency, product quality, and profitability could offer a more comprehensive understanding of how IM contributes to enterprise success. IM can strengthen production efficiency through automation and process optimization. Relevant indicators include equipment efficiency, production cycle time, and unit product cost. IM enhances product quality by enabling precise manufacturing and real-time monitoring. Key indicators include product qualification rate, return rate, and customer complaint rate. As a reflection of financial performance, profitability can be improved through reduced costs, enhanced production efficiency, and better product quality. Relevant indicators include net profit margin, gross profit margin,

and return on investment. Additionally, performance metrics should be tailored to specific industries, as priorities may differ. For example, in the electronics manufacturing industry, emphasis may be placed on product iteration cycles, R&D input-output ratios, and defect rates. In contrast, the automotive industry must strike a balance between production efficiency and quality.

(2) Examining the effects of IM on regional economic development, including its contributions to industrial upgrading, economic growth, and job creation, can provide valuable insights into policy decisions that promote sustainable economic development.

(3) Exploring the integrated application of IM with other emerging technologies, such as blockchain, cloud computing, and the Internet of Things (IoT), can further enhance corporate IE and competitiveness. This could lead to the development of novel strategies to maintain a leading edge in technological innovation. Synergies between blockchain and IM enhance data credibility, transparency, and intellectual property protection. In particular, blockchain can ensure transparency in the distribution of government subsidies, thereby strengthening resource allocation efficiency. Meanwhile, IoT enables real-time, data-driven decision making by continuously collecting production line data and integrating it with AI algorithms to dynamically optimize manufacturing processes. However, existing literature primarily focuses on the impact of individual technologies on IM, with limited empirical evidence on the effects of integrated technology applications. Recent studies on intelligent transformation emphasize the growing importance of digital technologies in shaping the future of manufacturing innovation [37]. Therefore, future research should investigate how integrated deployment of digitally empowered IM can fundamentally reshape corporate innovation ecosystems.

6.2 Conclusion

The imperative of China's high-quality development and the strategic direction of Made in China 2025 indicate the need to explore the potential of IM to enhance enterprise IE. This study, spanning 2015–2021, employed machine learning-based text mining techniques to assess the penetration of IM in enterprises. This study investigated its impact on IE, explored its mechanisms, and examined the moderating effects of financial development and industry competition. The results indicated that (1) IM consistently enhanced enterprise IE, as confirmed through robustness tests including instrumental variable method endogeneity tests and replacing the explained variables; (2) IM enhanced IE by accessing government resources and driving intellectual capital; and (3) the impact of IM on IE depended on the level of financial development and industry competition. Higher levels of financial development weakened the positive influence of IM on IE, while greater industry competition strengthened this effect.

6.3 Managerial implications

Chinese manufacturing enterprises should strategically invest in IM technologies to leverage AI-based solutions fully. Policymakers should continue to support initiatives to promote IM. Collaboration between industry, academia, and government can foster an innovative ecosystem. Based on this, we present the following specific policy recommendations:

(1) Proposing differentiated IM development strategies for various types of enterprises: Small and medium-sized enterprises (SMEs) require tailored IM strategies that address resource limitations through targeted policy design, technological adaptation, and ecosystem collaboration. For example, tiered subsidies and tax incentives can be structured to provide differentiated support based on enterprise size and technology investment ratios. Large enterprises receiving government subsidies should be required to offer technical training to SMEs within their supply chains to foster ecosystem-wide collaboration. Additionally, cloud-based solutions, such as manufacturing execution system, enterprise resource planning, and software as a

service platforms, should be made available to facilitate accessible and scalable technical implementation for SMEs. To evaluate the long-term effectiveness of such policies, key technological innovation indicators such as R&D investment intensity and patent output density can serve as core benchmarks. Collaboration with academic institutions should also be encouraged, with university research teams commissioned to publish White Papers on IM Policy every 3 years to ensure independent third-party evaluation. Furthermore, a dynamic benchmarking and monitoring system, combined with third-party verification, can support systematic tracking of policy effectiveness over time.

(2) Implementing precise and effective policies for government resource support: Special funds for smart manufacturing should be established to enhance support for innovation projects in SMEs. In addition, tax incentives, subsidies, and other policies should be provided to reduce innovation costs for businesses engaged in smart manufacturing.

(3) Creating a systematic and comprehensive plan for cultivating human capital: The development of talent training systems for smart manufacturing should be strengthened by encouraging universities and vocational colleges to offer specialized courses. Enterprises should be motivated to attract and nurture high-level talent through programs, scholarships, and other methods to support talent growth.

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