Front. Bus. Res. China 2026, 20(1): 1–30
DOI 10.3868/s070-021-026-0001-5

RESEARCH ARTICLE

Does Intelligent Manufacturing Improve Enterprise Innovation Efficiency? An Explanation Based on the Enterprise Life Cycle Theory*

LI Jiao[a], LIU Jianli[b]

Abstract

Intelligent manufacturing inherently embodies the techno-economic characteristics commonly associated with general information technologies, such as permeability, substitutability, and synergy. Yet when deployed in manufacturing, its adoption typically entails prolonged experimentation and validation, giving rise to delays and heterogeneous outcomes in both implementation and performance. Much of the existing literature asks whether intelligent manufacturing enhances enterprises' innovation efficiency, fueling broader debates over productivity. The more fundamental question, however, is when and for which types of enterprises intelligent manufacturing enhances innovation efficiency—that is, the question of its effectiveness. Based on data from A-share listed manufacturing companies over the period 2010–2023, this paper examines the impact of intelligent manufacturing on enterprises' innovation efficiency from the perspective of the enterprise life cycle. The empirical results show that intelligent manufacturing, on the whole, improves enterprises' innovation efficiency. From the life cycle perspective, intelligent manufacturing exerts a positive effect on enterprises in the mature stage, but has no significant impact on enterprises in the growth or decline stages. Differences in innovation incentives, R&D capabilities, and organizational characteristics across life cycle stages are the main reasons for this pattern. Heterogeneity analysis further indicates that intelligent manufacturing improves innovation efficiency among mature-stage non-state-owned enterprises, high-technology enterprises, and technology-intensive enterprises, while exerting no significant effect on other types or stages of enterprises. In terms of the underlying mechanism, intelligent manufacturing enhances enterprises' innovation efficiency by strengthening their knowledge absorptive capacity. The findings of this paper offer policy implications for promoting intelligent manufacturing in support of boosting China's strength in manufacturing.

Keywords intelligent manufacturing; innovation efficiency; life cycle theory; manufacturing; knowledge absorptive capacity

* This paper is translated from *经济与管理研究* [Research on Economics and Management], 2025, (7), 110–127.

[a] School of Business, University of Chinese Academy of Social Sciences, Beijing 102488, China

[b] Institute of Industrial Economics, Chinese Academy of Social Sciences, Beijing 100006, China

1 Introduction

Manufacturing industry sits at the heart of national economic development. Amid the surge of digitalization and intelligence, fostering R&D-driven innovation in manufacturing enterprises has become central to China's pursuit of high-quality growth and its ambition to climb the upper reaches of the global value chain. This digital-intelligent wave has spawned intelligent manufacturing as an advanced form of manufacturing and a new mode of production. Embodied in manufacturing equipment, industrial software, integrated solutions, and smart factories, intelligent manufacturing promises to inject fresh momentum into enterprise development and to raise innovation efficiency. In 2021, eight government departments, including the Ministry of Industry and Information Technology, jointly released the *Smart Manufacturing Development Plan for the "14th Five-Year Plan" Period*,[1] declaring intelligent manufacturing to be the principal thrust of boosting China's strength in manufacturing and a determinant of manufacturing quality. The report to the 20th National Congress of the Communist Party of China reinforces that "We will carry out industrial foundation reengineering projects and research projects on major technologies and equipment; support enterprises that use special and sophisticated technologies to produce novel and unique products; and move the manufacturing sector toward higher-end, smarter, and greener production" (Xi, 2022, p. 30). Together, these policy signals make clear that intelligent manufacturing is essential both to shoring up the real economy and to securing an edge in the next round of global manufacturing competition.

Past technological revolutions have done more than lift productivity. They have also fundamentally reconfigured the social division of labor and employment relations (Shen & Zhang, 2022). Innovation efficiency captures an enterprise's ability to generate patents and citations from each unit of R&D spending (Hirshleifer et al., 2013). Relative to labor inputs, R&D expenditure exerts a stronger influence on innovation efficiency, reflecting its higher output elasticity (Yang, 2013). As an advanced manufacturing form and production mode, intelligent manufacturing integrates a suite of next-generation information technologies, including the Internet of Things, big data, cloud computing, 5G, and artificial intelligence (AI). These technologies permeate the entire lifecycle of enterprise activities, from product design and production to management and services, linking enterprises, products, and consumers across value-chain networks and enabling deep integration of internal and external information (Müller et al., 2018). Intelligent manufacturing is not merely about technological breakthroughs. It entails a comprehensive enterprise transformation anchored in technological upgrading, combining information technologies with manufacturing technologies (Zeng & Zhou, 2024). By reshaping the production, recombination, and management of knowledge, it strengthens knowledge absorptive capacity in the innovation process (Joshi et al., 2010) and, in turn, raises enterprises' R&D productivity (Ravichandran et al., 2017).

Yet the question of whether intelligent manufacturing promotes innovation in manufacturing

[1] The corresponding Chinese title is "十四五" 智能制造发展规划 .

enterprises remains contested. On the one hand, scholars argue that intelligent manufacturing stimulates enterprise innovation by improving factor allocation and skill structures (Ding et al., 2023), easing financing constraints (Zhang et al., 2021), and attracting talent (Liang et al., 2024). Exploiting China's intelligent manufacturing demonstration projects as quasi-natural experiments, Zhang et al. (2021) and Yin and Li (2022) find significant gains in enterprise technological innovation. Survey-based evidence from Chen et al. (2021) likewise points to higher innovation performance, while Deng and Jiang (2022) show that intelligent transformation can markedly stimulate enterprise innovation. On the other hand, the inherently long-term and uncertain nature of intelligent manufacturing is emphasized. Disparities between investment costs and returns may induce rigidity in production and management systems and create technological overload, ultimately undermining innovation efficiency (Haug et al., 2023; Meng & Zhao, 2018). Du and Wang (2024) identify a U-shaped, rather than linear, relationship between intelligent manufacturing and innovation efficiency in manufacturing enterprises. Liu et al. (2024) further show that intelligent transformation promotes innovation overall, but that its breadth is beneficial whereas its depth may be inhibitory.

To reconcile these divergent findings, Haug et al. (2023) highlight enterprise technology orientation, defined as the capacity and inclination to acquire and deploy technological knowledge in the information age. This orientation helps explain whether small and medium-sized enterprises derive innovation benefits from IT use. Enterprises with a strong technology orientation tend to innovate more aggressively and are less constrained by IT complexity. While existing studies offer useful explanations, and some identify lagged effects between intelligent manufacturing and enterprise innovation (Zhang et al., 2021), short-term lags are insufficient to capture deeper temporal factors and heterogeneity. The mechanisms linking intelligent manufacturing to enterprise innovation therefore remain opaque. Opening this black box is essential to understanding how intelligent manufacturing can underpin new quality productive forces.

Against this backdrop, this paper contributes in three ways. Firstly, it interprets the relationship between intelligent manufacturing and enterprise innovation through enterprise life cycle theory, shifting the focus from whether intelligent manufacturing improves innovation efficiency to when and for which enterprises such improvements are effective. This perspective supplements the prevailing binary debate. Secondly, by measuring innovation efficiency using R&D-expenditure-scaled indicators that incorporate enterprises' prior inputs into patent applications and citations, the analysis more accurately reflects the innovation input–output relationship. Thirdly, rather than emphasizing mechanisms such as human capital upgrading, strategic transformation, or financial and information channels, this paper advances a knowledge absorptive capacity mechanism through which intelligent manufacturing enhances enterprise innovation efficiency, extending the existing literature. Taken together, an enterprise life cycle perspective not only offers a coherent explanation for the ongoing debate, but also provides practical guidance on how intelligent manufacturing can be leveraged to raise innovation efficiency.

2 Theoretical Framework and Research Hypotheses

2.1 Intelligent Manufacturing, Intelligence, and Measurement

Intelligent manufacturing refers to a new manufacturing form and mode of production organization arising from the deep integration of advanced information and communication technologies with manufacturing processes (Liu & Li, 2024). Viewed as an advanced manufacturing form, it disrupts traditional manufacturing forms through human–machine integration, industrial big data, service-oriented manufacturing, and mass customization. In doing so, it enables vertical integration of internal capital, information, and logistics flows, alongside end-to-end horizontal integration across intermediate stages of production (Kusiak, 2023). From the perspective of production modes, the growing deployment of sensors in equipment such as machine tools allows manufacturing systems to perceive, act, and communicate autonomously (Zhang et al., 2015). By linking physical manufacturing equipment with big data analytics in the digital realm via the internet, intelligent manufacturing has given rise to a transformative production mode, namely Cyber-Physical Production Systems (CPPSs) (Zheng et al., 2018). The literature approaches intelligent manufacturing from four broad perspectives. The first concerns its conceptual and theoretical foundations. Scholars have examined its core connotations (Kang et al., 2016; Liu & Li, 2024), knowledge structures (Wu et al., 2023), and enabling mechanisms (Pei et al., 2023; Zhang et al., 2023). Under the conditions created by next-generation information technologies, resource allocation, end-to-end manufacturing control, and enterprise decision-making models have undergone fundamental change (Yang et al., 2023), calling for renewed inquiry into the innovation logic of intelligent manufacturing within this new industrial logic. The second strand focuses on effects. Intelligent manufacturing produces both labor-substituting and job-creating effects (Pan et al., 2024), strengthens industrial resilience by diversifying industrial structures and upgrading skill profiles (Han et al., 2023), and may crowd out innovation investment. The third examines antecedents, with studies highlighting technological (Chen, 2017), organizational (Wang et al., 2022), and environmental drivers (Meng & Zhao, 2018). The fourth addresses measurements. Accurate measurement underpins the assessment of both the direct and indirect effects of intelligent manufacturing. Existing work employs approaches such as entropy-weighted index systems (Li, 2020), text mining techniques (Yu et al., 2020), and proxy variables (Wang & Dong, 2020) to capture the level of intelligent manufacturing. Wen et al. (2022), synthesizing academic research, policy documents, and annual reports of listed enterprises, identify a set of feature words related to AI, internet technologies, big data, and value-chain-based intelligent manufacturing technologies. Yang et al. (2024) develop an evaluation index system encompassing input, technological, and output dimensions.

2.2 Intelligent Manufacturing and Enterprise Innovation Efficiency

Innovation efficiency captures an enterprise's capacity to convert scarce innovation resources into valuable patent outputs (Gao & Chou, 2015). It comprises both the efficiency

of technological R&D, which links innovation inputs to innovation outputs, and the efficiency with which technological outcomes are translated into economic value (Wei et al., 2024). In the traditional industrial era, scholarship focused largely on how enterprise size, age, capital structure, R&D activity, and ownership structure shaped innovation efficiency (Xiao & Lin, 2014). Such conclusions implicitly assumed a slow pace of external information technology change. In practice, however, innovation efficiency is highly sensitive to the speed of technological progress. Faster technological change fundamentally reshapes production modes, operating models, and sources of competitive advantage (Zhou et al., 2018), thereby raising innovation efficiency. As information technologies have advanced, new technological forms such as informatization, automation, digitalization, and intelligentization have emerged. Their application in manufacturing has given rise to new paradigms, including digital transformation, intelligent upgrading, and intelligent manufacturing.

Enterprise innovation is driven by the interaction of multiple factors. Changes in innovation inputs alone provide an incomplete picture of innovation outcomes. What matters is the ability to strengthen input–output performance, making innovation efficiency a key indicator of how effectively enterprises deploy innovation resources (Duran et al., 2016; Zhou et al., 2018). Intelligent manufacturing enhances innovation efficiency by reshaping resource utilization and information transmission, improving resource efficiency, and reducing information uncertainty. On the production side, the widespread application of information technology, AI, and big data across manufacturing stages (He & Bai, 2021) underpins lean and agile production. It enables more accurate production planning, avoids excess capacity or shortages, allows real-time monitoring of production parameters, and applies data analytics and forecasting to optimize operations, ensuring more efficient use of resources. On the organizational side, intelligent manufacturing facilitates cross-departmental collaboration through enterprise information management systems (Zhou & Shan, 2023), improves information flows, and markedly alleviates information asymmetry and the persistence of information silos. Within the innovation process, intelligent manufacturing lowers information search costs (Goldfarb & Tucker, 2019), compresses coordination costs arising from uncertainty in R&D, enables enterprises to access partners' knowledge resources through interactive strategies (Wu et al., 2025), raises the marginal productivity of data, and encourages greater patenting activity. Together, these effects translate into higher innovation efficiency. On this basis, Hypothesis 1 is proposed.

H1: Intelligent manufacturing improves enterprise innovation efficiency.

The literature identifies several mechanisms through which intelligent manufacturing influences enterprise innovation efficiency. The first is human capital upgrading. Practices such as automation and the substitution of machines for labor generate employment creation and substitution effects (Pan et al., 2024; Wang & Dong, 2020; Yu et al., 2021), optimize human capital structures (Yin & Li, 2022), and attract talent (Liang et al., 2024), all of which support enterprise innovation. The second is strategic transformation. By

reshaping resource foundations, intelligent manufacturing prompts strategic renewal and the emergence of new strategic configurations (Xiao & Li, 2020). The third is the information channel. Intelligent manufacturing lowers information acquisition costs, improves the efficiency of gathering internal and external information (Yin & Li, 2022), and enhances information processing capabilities (Wu & Ji, 2024), thereby facilitating enterprise innovation. The fourth is the financing channel. Through improvements in supply chain coordination and bank–enterprise relationships, intelligent manufacturing helps enterprises secure subsidies and financial support (Yin & Li, 2022) and eases financing constraints (Zhang et al., 2021). The fifth is the cost channel. By mitigating cost stickiness (Quan & Li, 2022) and reducing internal organizational costs (Du & Wang, 2024), intelligent manufacturing can stimulate enterprise innovation. Some studies, however, argue that a cost-leadership mechanism may not operate directly. Instead, rising costs may pressure enterprises to substitute away from high-cost factors through innovation (Quan & Li, 2022). More fundamentally, intelligent manufacturing entails a comprehensive, multi-level reconfiguration of manufacturing equipment, industrial software, system solutions, and intelligent factories. It constitutes a complex, multi-layered integrated system spanning supply chain management, production planning, execution, and quality control. Intertwined technological and industrial chains give rise to a knowledge system that integrates multiple disciplines and advanced technologies. By aggregating knowledge dispersed across different activities, processing and interpreting complex data at speed, and transforming vast datasets into actionable knowledge, intelligent manufacturing breaks down information and knowledge silos. It strengthens cross-departmental sharing and collaboration, promotes knowledge absorption and transformation in the innovation process, expands the boundaries of enterprise knowledge absorptive capacity (Zahra & George, 2002), and ultimately enhances innovation efficiency. Knowledge absorptive capacity refers to an enterprise's ability to identify, assimilate, transform, and apply new scientific information. Enterprises with strong absorptive capacity facilitate the transfer of tacit knowledge (Kodama, 2008), foster industry–university–research cooperation, and improve efficiency. By enhancing knowledge leverage and recombination capabilities, absorptive capacity supports product line expansion and new product development (Zahra & George, 2002). Enterprises that excel at acquiring and absorbing knowledge are better positioned to detect external trends and internalize them to continuously update their knowledge base (Li & Li, 2025), helping them avoid capability traps, lower transformation costs, and raise innovation efficiency. Accordingly, Hypothesis 2 is advanced.

H2: Intelligent manufacturing enhances enterprise innovation efficiency by strengthening knowledge absorptive capacity.

2.3 Enterprise Life Cycle and Innovation Efficiency

The notion of the enterprise life cycle dates back to Haire (1959). Adizes (1990) subsequently

develops a comprehensive life cycle theory, arguing that as enterprises move from one stage to another, they confront distinct challenges. Failure to resolve these challenges through effective decision-making and a tendency to repeat past behaviors can stall organizational development (Adizes, 1990). Methods for classifying enterprise life cycles are generally divided into qualitative and quantitative approaches. Qualitative methods align an enterprise's current characteristics with the defining features of each life cycle stage, most notably in the framework proposed by Adizes (1990). Quantitative approaches include single-indicator methods, composite index methods, and cash flow pattern methods (Anthony & Ramesh, 1992; Chen & Chen, 2012; DeAngelo et al., 2006; Zhou et al., 2016).

In light of the contested relationship between intelligent manufacturing and innovation efficiency, this paper draws on enterprise life cycle theory to shift the analytical focus from whether intelligent manufacturing improves innovation efficiency to when and for which enterprises such effects materialize. Intelligent manufacturing embodies the techno-economic attributes of information technologies, including permeability, substitutability, and synergy (Shen & Zhang, 2022). Its application in manufacturing typically involves prolonged experimentation and validation, producing implementation lags (Zhang et al., 2021) and heterogeneous outcomes. As a result, the impact of intelligent manufacturing on innovation efficiency is likely to vary across stages of enterprise development. Much of the existing literature emphasizes individual heterogeneity, while paying insufficient attention to heterogeneity across life cycle stages. Enterprises at different stages face distinct internal and external risks and shocks (Duran et al., 2016), and differences in innovation willingness, R&D capability, and organizational characteristics shape innovation efficiency accordingly (Miller & Friesen, 1984).

At the growth stage, innovation efficiency is shaped by the dual constraints of dynamic resource scarcity and limited strategic focus. Although innovation willingness is strong, enterprises face a fundamental tension between rapid market expansion and constrained resources. Survival pressures channel innovation toward short-term value realization, fostering opportunistic technology choices and crowding out basic research investment. R&D capability is constrained by shallow knowledge accumulation, leading to linear patterns of technological iteration and persistent dependence on existing technological paths. Rapid organizational expansion further undermines coordination, slowing knowledge flows across departments and weakening alignment with strategic objectives. The decentralization of innovation decision-making heightens the risk of resource misallocation and, in turn, dampens innovation efficiency.

In the mature stage, enterprises typically sustain high innovation willingness while R&D resources and experience reach their zenith. Deep technological accumulation and systematized R&D capabilities enable the recruitment of specialized talent and the adoption of advanced equipment, accelerating innovation. Enhanced R&D capabilities directly translate into higher innovation efficiency, allowing enterprises to develop new products and improve technologies more effectively. Established institutions, organizational structures, and

stable production systems help absorb growth-related pressures and support the systematic management of innovation projects, strengthening R&D performance in both new business creation and product innovation. Moreover, mature-stage enterprises tend to exhibit a high degree of flexible automation, enabling rapid responses to market shifts while continuously accumulating and structuring knowledge. This process limits knowledge loss, speeds experience transfer, allows subsequent innovation to build on accumulated capabilities, reduces redundant experimentation, and raises innovation efficiency.

In the decline stage, enterprises often grapple with shrinking market shares and fading growth momentum. Innovation willingness is distorted by survival anxiety into defensive strategies. Managerial cognitive rigidity confines innovation to incremental improvements, while technology choices display excessive path dependence. R&D capability erodes as knowledge systems fragment, the loss of key personnel weakens technological decoding capacity, and aging equipment combined with delayed digitalization creates generational barriers to innovation. The breakdown of external knowledge networks further disconnects enterprises from mainstream innovation ecosystems. Hierarchical organizational structures slow decision-making, risk-averse cultures suppress experimentation in breakthrough innovation, and past successes harden into cognitive constraints. Innovation response mechanisms consequently fail. At this stage, innovation efficiency is undermined by a self-reinforcing cycle of capability deterioration that steadily compresses innovation space. The rigid accumulation of organizational memory obstructs the reassessment of technological paradigms, leading ultimately to irreversible decline in innovation capability. On this basis, the following hypotheses are advanced:

H3: Intelligent manufacturing has no significant effect on innovation efficiency in growth-stage enterprises.

H4: Intelligent manufacturing enhances innovation efficiency in mature-stage enterprises.

H5: Intelligent manufacturing has no significant effect on innovation efficiency in decline-stage enterprises.

3 Empirical Research Design

3.1 Sample Selection

In line with the industry classification standards issued by the China Securities Regulatory Commission (CSRC) in 2012, this paper draws on a sample of 3,666 A-share listed manufacturing companies spanning 2010–2023. The choice of period reflects two considerations. Firstly, large-scale adoption of industrial robots and intelligent manufacturing technologies only began after 2010. Secondly, China launched its first intelligent manufacturing policy pilots in 2015. Including observations from both before and after the pilot initiatives allows a clearer assessment of the effects of intelligent manufacturing on enterprise innovation efficiency and the channels through which those effects operate. The analysis combines data from three primary sources. (1) Measures of intelligent manufacturing

are constructed using keyword frequencies derived from academic studies, policy documents, and annual reports of listed enterprises, with company-level data for measuring intelligent manufacturing extracted from annual reports available on the CNINFO platform. (2) Patent citation data are obtained from the China Research Data Services Platform (CNRDS) provided by Shanghai Hehe Information Technology Co., Ltd. (3) Data on patent applications, mechanism variables, and control variables are taken from the China Stock Market and Accounting Research (CSMAR) database compiled by Shenzhen CSMAR Data Technology Co., Ltd. All datasets are carefully matched by stock code and year.

Several steps are taken to clean and refine the data. Firstly, following the CSRC's 2012 classification, the sample is restricted to A-share listed manufacturing enterprises, identified by two-digit industry codes beginning with "C." Secondly, Special Treatment enterprises are excluded. Thirdly, when extracting information from the Management Discussion and Analysis (MD&A) section of annual reports, enterprises that remained entirely in the strategic preparation stage of intelligent manufacturing are removed, as are observations corresponding to years in which enterprises were only temporarily in the preparation stage. Observations are retained once enterprises enter the strategic implementation stage, thereby avoiding the exclusion of entire enterprise histories. Fourthly, samples with severe data deficiencies and outliers are eliminated. Fifthly, to limit the influence of extreme observations, all continuous variables are winsorized at the 1st and 99th percentiles on a year-by-year basis. Finally, standard errors are clustered at the industry level to ensure robust inference. After these procedures, the final dataset comprises 3,071 enterprises and 21,745 observations.

3.2 Model Specification

To assess the effect of intelligent manufacturing on innovation efficiency in manufacturing enterprises, this paper builds on the framework developed by Wang and Dong (2020) and specifies the following econometric model:

$$Innov_mau_{it} = \beta_0 + \beta_1 IM_{it} + X'_{it}\beta + \mu_i + \gamma_t + \varepsilon_{it}. \quad (1)$$

Here, $Innov_mau_{it}$ denotes the innovation efficiency of manufacturing enterprises, while IM_{it} captures the level of intelligent manufacturing. X'_{it} is a vector of control variables encompassing enterprise operating characteristics and company governance factors. Enterprise fixed effects and year fixed effects are included to account for unobserved enterprise-specific conditions and economy-wide fluctuations over time. The error term is represented by ε_{it}. Consistent with the theoretical mechanisms and hypotheses outlined above, a significantly positive coefficient β_1 indicates that intelligent manufacturing enhances enterprise innovation efficiency. Conversely, a significantly negative β_1 would imply that intelligent manufacturing exerts a suppressing effect on enterprise innovation efficiency.

3.3 Variable Definitions

3.3.1 Dependent Variable

Manufacturing enterprise innovation efficiency *(Innov_mau$_{it}$)*. Much of the literature measures innovation efficiency using the logarithm of patent applications or patent citations (Du & Wang, 2024). Such measures, however, overlook the temporal dimension of the R&D inputs that underpin patenting activity. To account for this, this paper follows Hirshleifer et al. (2013) and constructs a measure of manufacturing enterprise innovation efficiency based on patent citations scaled by R&D expenditure. As a robustness check, patent grants scaled by R&D expenditure are used as an alternative indicator. Company-level patent citations better capture the technological and economic significance of patented innovations and thus provide a more informative proxy for innovation efficiency. Because citations accumulate gradually, and to ensure that innovation efficiency is fully observable to investors, this paper tracks all citations received by a patent from its grant date through the end of the sample period. Cumulative citation counts excluding self-citations are employed. Specifically, patent citations divided by R&D expenditure are defined as the ratio of the cumulative number of non-self-citations received by company i in year t to the relevant total R&D expenditure, as shown in equation (2). Following Gu (2005), the analysis controls for differences in citation propensity associated with technological fields, grant years, and citation years. The five-year window used in calculating company-level patent citations is consistent with prior evidence indicating that, in most industries, the effective technological cycle measured by the persistence of R&D benefits is around five years. The denominator, covering R&D expenditures from $t-3$ to $t-7$, reflects both the R&D investment contributing to successful patent applications and an assumed two-year lag between application and grant. For instance, patents granted in year $t-1$ are assumed to be associated with R&D spending in year $t-3$. Missing R&D values in the denominator are set to zero.

$$Innov_mau_{it} = \frac{Citation}{R\&D} = \frac{Citation_{it}}{R\&D_{i,t-3} + R\&D_{i,t-4} + R\&D_{i,t-5} + R\&D_{i,t-6} + R\&D_{i,t-7}}. \quad (2)$$

3.3.2 Independent Variable

Intelligent manufacturing (IM_{it}). Indicators closely related to intelligent manufacturing include the level of intelligence and AI. Existing studies mainly adopt four approaches to measuring enterprise-level intelligent manufacturing. The first uses the Bartik instrumental variable method to calculate robot installation density or penetration (Mann & Püttmann, 2023; Wang & Dong, 2020). The second identifies enterprise AI patent data (Mann & Püttmann, 2023). The third applies text analysis to measure the frequency of AI-related keywords as a proxy for the intensity of enterprises' application of intelligent manufacturing technologies (Yao et al., 2024). The fourth measures enterprises' investment levels in AI by collecting news announcements related to AI investment disclosed by listed companies (Lui et al., 2022). Company annual reports constitute the core documents through which listed companies disclose their operating conditions to external stakeholders. Their functions span legal

compliance, investment decision-making, and strategic communication. Against this backdrop, and following Yu et al. (2020), this paper adopts a text mining approach to construct an intelligent manufacturing index based on keyword frequencies. The construction of the index relies on three main data sources: academic literature, policy documents, and listed company annual reports. With respect to academic literature, this paper draws on discussions of the conceptual connotations and indicator construction of intelligent manufacturing by Yu et al. (2020), Wu et al. (2021), Song and Du (2021), and Liu and Li (2024). Based on these studies, an initial set of keywords related to intelligent equipment technologies, AI technologies, industrial software technologies, and value chain intelligent manufacturing technologies is identified. With respect to policy documents and research reports, this paper takes *Made in China 2025*, the S*mart Manufacturing Development Plan (2016–2020)*,[2] and other recent policy documents related to intelligent manufacturing as references, further enriching the feature lexicon associated with the above technologies. For listed company annual reports, keyword expansion follows three steps. Firstly, Python is used to scrape the MD&A section of annual reports from the CNINFO website. Secondly, terms related to intelligent manufacturing are extracted from relevant policy documents and authoritative literature, as summarized in Table 1, to construct a dedicated lexicon. This lexicon is then integrated into the Jieba word segmentation system to improve the effectiveness of text segmentation for MD&A content. Thirdly, a Word2Vec bag-of-words model is applied to the segmented text to extract associated terms. Combined with manual screening, keyword combinations closely related to intelligent equipment technologies, AI technologies, industrial software technologies, and value chain intelligent manufacturing technologies are selected. Based on the above text mining procedures, the data are cleaned and denoised in two respects. Firstly, irrelevant textual information is removed, including stop words such as *de* (的), *le* (了), and *he* (和), punctuation marks, and advertising language. Expressions in which keywords are preceded by negation terms such as *wu* (无), *bu* (不), or *fei* (非) are also excluded. Secondly, invalid samples corresponding to enterprises in the strategic planning stage are excluded, and the analysis focuses on enterprises that have entered the implementation stage and beyond, ensuring that the results reflect the actual deployment of intelligent manufacturing.

Table 1

Core Keywords for Intelligent Manufacturing

Indicator	Measurement dimension	Feature keywords
Intelligent manufacturing	Intelligent equipment technologies	Industrial robots, numerical control machine tools, automated guided vehicles, 3D printing equipment, intelligent sensors, machine vision systems, collaborative robots, edge computing devices, digital twin equipment, predictive maintenance systems, flexible manufacturing units, intelligent tooling and fixtures, intelligent welding equipment, intelligent terminals

(*To be continued*)

[2] The corresponding Chinese title is 智能制造发展规划（2016–2020 年）.

(*Continued*)

Indicator	Measurement dimension	Feature keywords
	AI technologies	Machine learning, deep learning, AI, natural language processing, intelligent transformation, computer vision, reinforcement learning, recommendation systems, sentiment analysis, speech recognition, image generation, autonomous driving, machine translation, anomaly detection, knowledge graphs, facial recognition, automatic text summarization, chatbots, time-series forecasting, deepfake detection, object detection, data augmentation
	Industrial software technologies	Computer-aided design, computer-aided manufacturing, manufacturing execution systems, enterprise resource planning, product life cycle management, supply chain management, distributed control systems, industrial internet of things platforms, process control software, automated design software, numerical control programming software, real-time monitoring systems, asset management systems, data acquisition and monitoring systems, quality management systems, production planning and scheduling systems, equipment maintenance management software, energy efficiency management systems, industrial cybersecurity software, virtual simulation systems
	Value chain intelligent manufacturing technologies	Intelligent engineering, intelligent manufacturing system solutions, supply chain management systems, intelligent marketing, production planning and scheduling systems, intelligent warehousing systems, logistics management systems, automated production lines, intelligent quality inspection systems, smart home technologies, industrial internet of things platforms, data acquisition and analysis systems, machine vision inspection, automated assembly technologies, product traceability systems, AI optimization algorithms, edge computing, digital twin technologies, intelligent distribution, energy consumption management systems, collaborative design platforms, virtual simulation systems, predictive maintenance technologies, robotic process automation, flexible manufacturing technologies

3.3.3 Grouping Variable

Following Zhou et al. (2016) and Liu et al. (2020), this paper classifies the enterprise life cycle using the cash flow pattern approach. Enterprises are assigned to different life cycle stages based on the sign combinations of net operating cash flow, net investing cash flow, and net financing cash flow. For the purposes of analysis, the life cycle is consolidated into three broad stages: growth, maturity, and decline, as summarized in Table 2.

Table 2
Cash Flow Patterns across Enterprise Life Cycle Stages

Cash flow category	Growth stage		Mature stage	Decline stage				
	Start-up	Expansion		Decline 1	Decline 2	Decline 3	Exit	Exit
Net operating cash flow	−	+	+	−	+	+	−	−
Net investing cash flow	−	−	−	−	+	+	+	+
Net financing cash flow	+	+	−	−	+	−	+	−

3.3.4 Control Variables

To account for other determinants of enterprise innovation efficiency, this paper draws on Quan and Li (2022) and Wang and Qin (2023) and incorporates a set of standard control variables. These include enterprise size (*Size*), enterprise age (*Age*), return on assets (*Roa*), cash flow (*SF*), Tobin's Q (*Tobin_Q*), retained earnings (*RE*), and asset structure (*Ppe*).

The specific definitions of all variables are reported in Table 3.

Table 3
Variable Definitions

Variable type	Variable name	Variable symbol	Variable measurement
Dependent variable	Manufacturing enterprise innovation efficiency	*Innov_mau*	Patent citations scaled by R&D expenditure
Independent variable	Intelligent manufacturing	*IM*	Information extraction from intelligent manufacturing texts
Mechanism variable	Knowledge absorptive capacity	*TAC*	R&D expenditure / operating revenue
Control variables	Enterprise size	*Size*	Natural logarithm of total assets
	Enterprise age	*Age*	Natural logarithm of years since establishment of the sample year
	Return on assets	*Roa*	Total liabilities / total assets
	Cash flow	*SF*	Net cash flow from operating activities / total assets
	Tobin's Q	*Tobin_Q*	Market value / total assets
	Retained earnings	*RE*	Retained earnings / total assets
	Asset structure	*Ppe*	Fixed assets / total assets

4 Results and Analysis

4.1 Descriptive Statistics

Table 4 presents the descriptive statistics. The average innovation efficiency of manufacturing enterprises (*Innov_mau*) is 3.4563, with a standard deviation of 6.6383. The large spread between the minimum value of 0.0771 and the maximum of 50.6445 points to pronounced heterogeneity in innovation efficiency across manufacturing enterprises, a pattern consistent with prior research. The intelligent manufacturing variable (*IM*) has a maximum value of 4.3567 and a standard deviation of 1.1503, indicating that mentions of intelligent manufacturing constitute a relatively small share of enterprises' annual report disclosures. This finding is in line with the notion that returns to intelligent manufacturing investment materialize with a lag (Wen et al., 2022), and suggests that some enterprises may understate their intelligent manufacturing inputs and progress in formal reports. The descriptive statistics of the control variables broadly accord with those documented in the existing literature.

Table 4

Descriptive Statistics of Variables

Variable	*N*	*M*	*SD*	*Min.*	*Mdn*	*Max.*
IM	21,745	0.8835	1.1503	0.0000	0.0000	4.3567
Innov_mau	21,745	3.4563	6.6383	0.0771	1.6062	50.6445
Size	21,745	22.1425	1.1648	20.0439	21.9764	25.7377
Age	21,745	2.8867	0.3403	1.7918	2.9444	3.5264
Roa	21,745	0.3543	0.2002	0.0432	0.3256	1.0008
SF	21,745	0.0515	0.0647	–0.1261	0.0486	0.2406
Tobin_Q	21,745	2.1077	1.2608	0.8657	1.7019	8.0438
RE	21,745	0.1811	0.2112	–0.8637	0.1953	0.6077
Ppe	21,745	0.2191	0.1275	0.0180	0.1967	0.5984

4.2 Baseline Regression Analysis

Table 5 presents the baseline regression estimates for the effect of intelligent manufacturing on innovation efficiency in manufacturing enterprises. The coefficient on intelligent manufacturing (*IM*) in the full sample is positive and statistically significant at the 10% level, indicating that intelligent manufacturing is associated with higher enterprise innovation efficiency (*Innov_mau*). Quantitatively, a one-percentage-point increase in intelligent manufacturing corresponds to a 0.116 percentage-point rise in innovation efficiency, lending support to *H1*. A life-cycle disaggregation reveals a more nuanced pattern. Intelligent manufacturing exerts a positive and highly significant effect on innovation efficiency only among enterprises in the mature stage, with the coefficient significant at the 1% level. By contrast, the coefficients for enterprises in the growth and decline stages are statistically

insignificant. For mature-stage enterprises, a one-percentage-point increase in intelligent manufacturing raises innovation efficiency by 0.2315 percentage points, corroborating *H3* to *H5*. Enterprises in the growth stage typically channel scarce resources toward product iteration, capacity expansion, and market development. Intelligent manufacturing, however, demands substantial upfront investment in digital infrastructure, cross-system integration, and organizational process reengineering. Its high initial costs and long payback horizon sit uneasily with a short-term, survival-oriented strategy. Enterprises in the decline stage, meanwhile, confront shrinking market share, strained cash flows, and talent attrition. As organizational capabilities erode and managerial rigidity sets in, risk tolerance diminishes, rendering such enterprises particularly sensitive to the trial-and-error costs associated with intelligent manufacturing and further limiting their capacity to stimulate innovation. Mature-stage enterprises present a contrasting picture. Stable cash flows, economies of scale in production, and well-established management systems allow them to absorb the high costs of intelligent manufacturing. The alignment between a robust resource base, mature organizational structures, and the strategic imperative to overcome innovation bottlenecks enables the technological advantages of intelligent manufacturing to translate into tangible gains in innovation efficiency.

Table 5
Baseline Regression Results

Dependent variable	Full sample	Growth stage	Mature stage	Decline stage
IM	0.1160*	0.0984	0.2315***	0.0011
	(0.0582)	(0.0795)	(0.0842)	(0.2070)
Size	–0.0418	–0.2321	0.2029	–0.3536
	(0.2425)	(0.2485)	(0.4159)	(1.2343)
Age	9.1920***	7.3611***	11.7261***	–6.3271
	(1.5110)	(2.1140)	(2.1813)	(7.2791)
Roa	1.6983***	1.3218*	2.1212**	–2.5892
	(0.5984)	(0.7322)	(0.9781)	(2.4390)
SF	–0.9313	0.5510	–2.5672**	–1.8150
	(0.7943)	(1.3948)	(1.2536)	(3.7690)
Tobin_Q	0.1422**	0.0989	0.1332*	0.5303*
	(0.0699)	(0.1177)	(0.0772)	(0.2852)
RE	–0.9616*	–0.3326	–1.6516**	–1.8334
	(0.5026)	(0.5545)	(0.7414)	(6.2468)
Ppe	–2.9376**	–3.5441**	–1.7242	–3.7474
	(1.2926)	(1.5347)	(1.9606)	(4.5667)
Constant	–22.2744***	–11.5365	–36.5431***	31.0782
	(7.2719)	(9.2593)	(11.4237)	(37.2075)
Year fixed effects	Yes	Yes	Yes	Yes

(*To be continued*)

(*Continued*)

Dependent variable	Full sample	Growth stage	Mature stage	Decline stage
Enterprise fixed effects	Yes	Yes	Yes	Yes
n	21,481	9,473	10,294	666
Adj. R^2	0.5742	0.6556	0.6011	0.6705

Note. Robust standard errors are reported in parentheses.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

4.3 Endogeneity Analysis

A potential endogeneity concern arises from reverse causality between intelligent manufacturing and enterprise innovation efficiency. Intelligent manufacturing can directly raise innovation efficiency by shortening R&D cycles and lowering trial-and-error costs through data-driven process optimization. At the same time, enterprises with stronger innovation efficiency are often endowed with greater knowledge absorptive capacity and resource slack, making them more inclined to invest in intelligent manufacturing to facilitate technological upgrading. To address reverse causality and omitted-variable bias, this paper follows Huang et al. (2019) and constructs an instrumental variable based on the number of post offices per million people in the enterprise's home province in 1984. Post office density in 1984 captures the quality of early communication infrastructure in a region. As a historical endowment, it influences the later penetration of intelligent manufacturing technologies by promoting information exchange and technology diffusion, thereby satisfying the relevance condition of instrumental variables and endogenous variables. At the same time, the number of post offices is a lagged variable that predates the rise of intelligent manufacturing and bears no direct relationship to current enterprise innovation efficiency. This satisfies the exclusion restriction and mitigates bias stemming from contemporaneous confounders such as economic development or education investment, allowing the bidirectional causal link between intelligent manufacturing and innovation efficiency to be effectively isolated. However, given the use of balanced panel data, a time-invariant measure of post office density would be absorbed by enterprise fixed effects, undermining identification and potentially generating weak-instrument problems. To overcome this limitation, a time-varying component is introduced to construct a panel instrumental variable. Drawing on Nunn and Qian (2014), the instrument is defined as the interaction between provincial post office density in 1984, which varies across enterprises, and lagged internet investment, which varies over time. This interaction restores identifying variation while maintaining the core assumptions of instrumental variable estimation. After controlling for relevant confounding factors, the instrument is both theoretically grounded and statistically sound, enabling identification of the net effect of intelligent manufacturing on enterprise innovation efficiency.

Table 6 reports the two-stage least squares (2SLS) estimates. In the full sample, the first-

stage results show that the instrumental variable is strongly correlated with intelligent manufacturing, with coefficients significant at the 1% level and F statistics exceeding the conventional threshold of 10. In the second stage, intelligent manufacturing continues to exert a positive and significant effect on enterprise innovation efficiency at the 1% level, in line with the baseline findings. The Kleibergen–Paap rk LM statistic rejects the null of underidentification at the 1% level, while the Kleibergen–Paap rk Wald F statistic exceeds the Stock–Yogo critical value at the 10% level, indicating that weak instrument concerns are unlikely. A life-cycle breakdown yields a consistent pattern. Although the first-stage relationship between the instrument and intelligent manufacturing is significant across enterprises in the growth, mature, and decline stages, second-stage significance is observed only for mature-stage enterprises. For this group, the under- identification hypothesis is rejected and the weak instrument test is passed. Taken together, these results confirm the reliability and validity of the chosen instrumental variable. Importantly, once endogeneity is addressed, the core conclusions of this paper remain intact.

Table 6

Regression Results of Endogeneity Analysis

Variable	First stage				Second stage			
	Full sample	Growth stage	Mature stage	Decline stage	Full sample	Growth stage	Mature stage	Decline stage
IM					0.1814***	0.0910	0.2505***	0.5753
					(0.0626)	(0.0838)	(0.0799)	(0.4183)
IV	0.0519***	0.0032***	0.0517***	0.0456***				
	(0.0014)	(0.0004)	(0.0019)	(0.0038)				
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM					11.9070***	10.8490***	12.1710***	0.9210***
Kleibergen-Paap rk Wald F					3,274.0170	3,595.7090	1,776.0630	772.0060
n	15,444	6,547	8,153	739	15,444	6,547	8,153	739

Note. Robust standard errors are reported in parentheses.

*** $p < 0.01$.

4.4 Robustness Test

To ensure the reliability and stability of the conclusions, this paper conducts robustness tests by replacing the measurement of the dependent variable and by changing the sample period. These tests are designed to verify that the empirical conclusions remain consistent under different conditions.

4.4.1 Replacing the Dependent Variable

This paper uses patents granted scaled by R&D capital (*Innov_patent*) as the robustness indicator. Patents/RDC is defined as the ratio of patents granted to company i in year t to its R&D capital in fiscal year $t-2$ (five-year cumulative R&D expenditure, assuming an annual depreciation rate of 20%), as shown in equation (3). Here, $R\&D_{i,\,t-2}$ denotes company i's R&D expenditure in the fiscal year ending in $t-2$, and so on. When constructing the denominator, missing R&D values are set to zero. A two-year gap between R&D capital and patent grants is allowed because the China National Intellectual Property Administration takes, on average, two years to grant patent applications. Using cumulative R&D expenditure as the denominator is based on the previous five years of R&D expenditure, all of which contributes to the successful filing of patent applications in year $t-2$ (which are approved in year t, implying a two-year application-to-grant lag).

$$Innov_patent_{it} = \frac{Patents_{it}}{RDC} = \frac{Patents_{it}}{R\&D_{i,\,t-2} + 0.8R\&D_{i,\,t-3} + 0.6R\&D_{i,\,t-4} + 0.4R\&D_{i,\,t-5} + 0.2R\&D_{i,\,t-6}}. \quad (3)$$

Stage-specific regression results are reported in Table 7. The regression coefficient of intelligent manufacturing (*IM*) is positive and statistically significant at the 1% level. Focusing on the enterprise life cycle, intelligent manufacturing (*IM*) increases innovation efficiency (*Innov_patent*) for enterprises in the mature stage, but has no effect on enterprises in the growth or decline stages. These results indicate that, after replacing the dependent-variable measure, the conclusions remain consistent with the baseline regression.

4.4.2 Changing the Sample Period

In December 2016, the Ministry of Industry and Information Technology and the Ministry of Finance issued the *Smart Manufacturing Development Plan (2016–2020)*, which may bias the empirical results. Accordingly, this paper excludes observations from 2016 and conducts a robustness check by changing the sample period. As shown in Table 7, the regression coefficient of intelligent manufacturing (*IM*) on innovation efficiency in manufacturing enterprises is positive and statistically significant at the 10% level. From an enterprise life cycle perspective, intelligent manufacturing (*IM*) increases innovation efficiency for mature-stage enterprises, but has no effect on enterprises in the growth or decline stages. The results suggest that the conclusions remain valid after changing the sample period.

Table 7
Robustness Test Regression Results

Variable	Replacing dependent variable				Changing sample period			
	Full sample	Growth stage	Mature stage	Decline stage	Full sample	Growth stage	Mature stage	Decline stage
IM	0.1327*** (0.0433)	–0.2078 (0.1437)	0.1859*** (0.0674)	–0.4003 (0.3562)	0.1115* (0.0627)	0.0984 (0.0806)	0.2139** (0.0928)	–0.0098 (0.2287)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	21,481	9,473	10,294	666	20,117	8,859	9,590	613
Adj. R^2	0.6320	0.5587	0.6509	0.8476	0.5705	0.6554	0.5973	0.6829

Note. Robust standard errors are reported in parentheses.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

5 Further Tests

5.1 Mechanism Analysis

To unpack how intelligent manufacturing influences enterprise innovation efficiency, this paper adopts the empirical strategy of Jiang (2022) and centers on knowledge absorptive capacity as the key transmission channel. The following model is specified to test the mechanism:

$$M_{it} = \beta_0 + \beta_1 IM_{it} + X'_{it}\beta + \mu_i + \gamma_t + \varepsilon_{it}. \quad (4)$$

M_{it} captures enterprise knowledge absorptive capacity, and all other variables are defined as in the baseline model. The estimation results are reported in Table 8. The full-sample regressions show that intelligent manufacturing significantly strengthens enterprises' knowledge absorptive capacity. Stage-specific estimates indicate that this effect holds across the growth, mature, and decline stages. However, only mature-stage enterprises are able to convert enhanced absorptive capacity into higher innovation efficiency. This finding aligns with the seminal definition by Zahra and George (2002), who conceptualize knowledge absorptive capacity as a dynamic capability linked to knowledge creation and exploitation and hence to the acquisition and preservation of enterprise competitive advantage. Subsequent studies demonstrate that enterprises with strong absorptive capacity are more flexible in reconfiguring their resource base and deploying capabilities at lower cost. Through effective resource orchestration, such enterprises can capitalize on emerging strategic opportunities, sustain superior performance, and raise innovation efficiency (Kodama, 2008). Evidence from Xie and Zuo (2013), based on 379 electronic information enterprises in the Yangtze River

Delta, further shows that stronger absorptive capacity enables enterprises to acquire external technologies and information more rapidly, accelerate product and process innovation, and ultimately enhance innovation efficiency. Taken together, the mechanism analysis confirms *H2*.

Table 8

Mechanism Test Regression Results

Variable	Full sample		Growth stage		Mature stage		Decline stage	
	Innov_mau	*TAC*	*Innov_mau*	*TAC*	*Innov_mau*	*TAC*	*Innov_mau*	*TAC*
IM	0.1160*	0.0183***	0.0984	0.0225*	0.2315***	0.0138**	0.0011	0.0394*
	(0.0582)	(0.0060)	(0.0795)	(0.0115)	(0.0842)	(0.0057)	(0.2070)	(0.0214)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	21,481	21,481	9,473	9,473	10,294	10,294	666	666
Adj. R^2	0.5742	0.9595	0.6556	0.9596	0.6011	0.9673	0.6705	0.9826

Note. Robust standard errors are reported in parentheses.

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

5.2 Heterogeneity Analysis

To gain a deeper understanding of how intelligent manufacturing affects innovation efficiency across different types of enterprises, this paper conducts heterogeneity analysis along three dimensions: state-owned versus non-state-owned enterprises, high-technology versus non-high-technology enterprises, and labor-intensive, capital-intensive, and technology-intensive enterprises.

5.2.1 State-Owned and Non-State-Owned Enterprises

Enterprises are classified by ownership and control. State-owned enterprises are assigned *SOE* = 1, while non-state-owned enterprises take *SOE* = 0. The estimates in Table 9 indicate that intelligent manufacturing significantly improves innovation efficiency among non-state-owned enterprises, but has no discernible effect on state-owned enterprises. This pattern reflects China's institutional realities. Operating in highly competitive markets, non-state-owned enterprises face strong innovation pressure. Flatter decision-making hierarchies accelerate technological responses, flexible incentive systems unlock human-capital potential, and focused resource-allocation strategies interact synergistically with open innovation

networks. Together, these features allow intelligent manufacturing to translate more readily into innovation gains. State-owned enterprises, by contrast, are constrained by multiple objectives and bureaucratic inertia. Innovation input may become detached from market signals, protracted approval chains slow technological commercialization, and risk aversion dampens exploratory activity. Under such conditions, the technological advantages of intelligent manufacturing are less likely to be fully converted into innovation momentum.

A life-cycle perspective further refines this picture. Intelligent manufacturing enhances innovation efficiency in both state-owned and non-state-owned enterprises at the mature stage, but has no significant impact during the growth or decline stages. Mature enterprises benefit from accumulated resources and well-established management systems. The widespread use of information technologies, AI, and big data in production, coupled with strong innovation incentives, enables intelligent manufacturing to support lean and agile manufacturing. Enterprises can formulate precise production plans, avoid excess capacity or stockouts, monitor key production parameters in real time, and optimize operations through data-driven forecasting, ensuring efficient resource utilization. By contrast, enterprises in the growth stage often lack the technological foundations and organizational maturity required to support intelligent manufacturing, despite their flexibility. Enterprises in the decline stage face contracting demand and tightening resource constraints, making it unlikely that intelligent manufacturing alone can reverse their broader downward trajectory.

5.2.2 High-Technology and Non-High-Technology Enterprises

In accordance with the *Classification of High-Technology Industries (Manufacturing, 2017)*,[3] enterprises are divided into high-technology and non-high-technology categories. The regression results reported in Table 9 show that intelligent manufacturing improves innovation efficiency in high-technology enterprises, but has no significant effect on non-high-technology enterprises. This is because high-technology enterprises are typically concentrated in technology-intensive sectors, such as information technology, biomedicine, new materials, and aerospace. These enterprises are characterized by technology-driven development, rapid iteration, and high talent intensity. Intelligent manufacturing can effectively optimize R&D processes and enhance the commercialization of technological outputs in such contexts. A life-cycle breakdown shows that this effect is concentrated in mature-stage high-technology enterprises. By this stage, these enterprises have built robust technological foundations and accumulated rich data resources, making them well suited to the technical demands of intelligent manufacturing. Its deployment therefore interacts synergistically with existing innovation capabilities. Automation and digital systems accelerate experimentation and testing, shortening development cycles and raising the conversion rate of innovative outputs.

[3] The corresponding Chinese title is 高技术产业（制造业）分类（2017）.

5.2.3 Labor-Intensive, Capital-Intensive, and Technology-Intensive Enterprises

Drawing on Qi et al. (2023), manufacturing enterprises are further classified by factor intensity into labor-intensive, capital-intensive, and technology-intensive groups, and grouped regressions are conducted across life cycle stages. As shown in Table 9, intelligent manufacturing significantly improves innovation efficiency only among technology-intensive enterprises, while having no significant effect on labor-intensive or capital-intensive enterprises. For technology-intensive enterprises, knowledge and R&D capability constitute the core productive inputs. The key technologies embedded in intelligent manufacturing are closely aligned with these enterprises' technological systems, allowing intelligent manufacturing to function as the "intelligent hub" of the innovation chain. Its data-driven decision-making and cross-disciplinary knowledge integration directly affect central innovation-efficiency metrics, such as R&D productivity and patent conversion efficiency, generating a strong enabling effect. Labor-intensive enterprises, by contrast, rely heavily on manual operations, with production processes that are highly standardized and technologically simple. Although intelligent manufacturing can replace certain routine tasks, cost considerations and capability constraints limit its impact to factor substitution, yielding only modest innovation gains. Capital-intensive enterprises depend on large-scale fixed-asset investment to realize economies of scale. Their innovation efficiency is more closely tied to improvements in capacity utilization and capital turnover than to the pace of technological innovation, leaving limited scope for intelligent manufacturing to generate incremental innovation benefits. The life-cycle analysis reinforces this interpretation. Intelligent manufacturing delivers a substantial boost to innovation efficiency only in mature-stage technology-intensive enterprises. These enterprises typically combine deep technological accumulation with demand for high value-added products, and their innovation efforts focus on R&D investment and high-precision production. At this stage, intelligent manufacturing accelerates the innovation process, while end-to-end data monitoring and feedback systems improve process optimization. The result is faster innovation iteration and higher innovation efficiency among mature-stage technology-intensive enterprises.

6 Conclusions and Policy Implications

Enterprise innovation underpins China's push toward high-quality manufacturing growth. The central challenge is how to motivate manufacturing enterprises to raise innovation efficiency and move the growth model from extensive expansion to efficiency-driven development. Intelligent manufacturing, as a new production paradigm, is pivotal to both product breakthroughs and process innovation. Yet its diffusion takes time, and enterprise investment in intelligent manufacturing does not automatically translate into immediate gains in innovation efficiency. Against this backdrop, and amid persistent debate over the innovation effects of intelligent manufacturing, this paper analyzes its impact through the lens of the enterprise life cycle, drawing on panel data for listed manufacturing enterprises from 2010 to 2023. Four conclusions emerge. Firstly, intelligent manufacturing raises innovation efficiency among manufacturing enterprises on average. Secondly, the effect is strongly stage-

Table 9

Heterogeneity Analysis Regression Results

Variable	State-owned enterprises				Non-state-owned enterprises			
	Full sample	Growth stage	Mature stage	Decline stage	Full sample	Growth stage	Mature stage	Decline stage
IM	0.2434 (0.2425)	0.2175 (0.3940)	0.3531* (0.1924)	–0.4681 (0.6963)	0.1690*** (0.0433)	0.0789 (0.0886)	0.1452** (0.0672)	–0.2493 (0.3692)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise/year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	5,541	1,570	3,416	291	16,150	7,860	7,289	366
R^2_{within}	0.0183	0.0296	0.0183	0.0310	0.0169	0.0069	0.0305	0.0694

Variable	High-technology enterprises				Non-high-technology enterprises			
	Full sample	Growth stage	Mature stage	Decline stage	Full sample	Growth stage	Mature stage	Decline stage
IM	0.1650** (0.0705)	0.1327 (0.0780)	0.2217* (0.1116)	–0.6087 (0.3394)	0.0166 (0.1748)	–0.1090 (0.2525)	0.2347 (0.2135)	–0.3504 (0.6482)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise/year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	15,501	7,025	7,225	469	5,961	2,418	3,035	192
R^2_{within}	0.0166	0.0119	0.0210	0.0253	0.0269	0.0313	0.0272	0.1643

(*To be continued*)

(*Continued*)

Variable	Labor-intensive enterprises				Capital-intensive enterprises				Technology-intensive enterprises			
	Full sample	Growth stage	Mature stage	Decline stage	Full sample	Growth stage	Mature stage	Decline stage	Full sample	Growth stage	Mature stage	Decline stage
IM	0.1807 (0.1483)	0.2007 (0.2652)	0.1469 (0.2376)	–0.4393 (0.4334)	–0.1743 (0.3117)	–0.4644 (0.3683)	0.1347 (0.3969)	–0.0141 (0.1977)	0.1813* (0.0837)	0.1473 (0.0859)	0.2372* (0.1168)	–0.5359 (0.3544)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise/year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	4,315	1,642	2,283	167	3,890	1,754	1,835	89	13,240	6,029	6,121	401
R^2_{within}	0.0180	0.0336	0.0158	0.0905	0.0237	0.0098	0.0431	0.6900	0.0054	0.0207	0.0244	0.0181

Note. Robust standard errors are reported in parentheses.

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

dependent: Intelligent manufacturing improves innovation efficiency only at the mature stage, with no significant impact during the growth or decline stages. Thirdly, heterogeneity analysis shows that these gains are concentrated among mature-stage non-state-owned enterprises, high-technology enterprises, and technology-intensive enterprises. Fourthly, intelligent manufacturing works by strengthening enterprises' knowledge absorptive capacity, which in turn enhances innovation efficiency.

These findings carry several policy implications for China's strategy to boost strength in manufacturing.

The first is strategic resolve. China should remain committed to advancing intelligent manufacturing and boosting the country's strength in manufacturing; the government should assume a leadership role in guiding enterprises toward intelligent transformation. This requires formulating clear development plans for intelligent manufacturing, specifying strategic objectives and priority areas, and promoting research and application of intelligent manufacturing technologies. Improving the legal, regulatory, and standards framework related to intelligent manufacturing and optimizing the market and business environment will help accelerate technology diffusion. Policymakers should also focus on key industries and regions, establish intelligent manufacturing demonstration zones and pilot projects, and promote replicable and scalable intelligent manufacturing models.

The second is institutional infrastructure for knowledge diffusion. China should leverage national industrial internet platforms to build "intelligent knowledge-sharing centers" and implement a "hundreds of cities, thousands of enterprises" knowledge-empowerment initiative. Given the high share of small and medium-sized enterprises and the uneven distribution of regional innovation resources, regional intelligent manufacturing knowledge-sharing centers could be established in cities hosting intelligent manufacturing clusters, building on the national data center for the industrial internet led by the Ministry of Industry and Information Technology. Enterprises receiving dedicated intelligent manufacturing subsidies should be required to open non-core process data, which, after anonymization, can be incorporated into industry knowledge bases. These centers could then provide local enterprises with standardized knowledge services, such as intelligent equipment knowledge graphs and process-optimization case packages, free of charge. By strengthening enterprises' external knowledge absorptive capacity, such initiatives would enhance innovation efficiency.

The third implication concerns policy precision. Policies designed to improve enterprise innovation efficiency through intelligent manufacturing should account for enterprise heterogeneity and life cycle characteristics, in order to improve policy effectiveness and precision. Differentiated policy mixes should be tailored to the institutional endowments of different enterprise types, including state-owned enterprises, private enterprises, and small and micro enterprises. For state-owned enterprises, the emphasis should be on alleviating institutional constraints and strengthening the synergy between intelligent manufacturing and market-oriented reforms. For private enterprises, policies should focus on lowering barriers to technological upgrading and unleashing their agile innovation advantages. For small and

micro enterprises, an inclusive support system is essential to prevent resource constraints from creating a digital divide. Policy priorities should also be aligned with enterprises' life cycle stages: growth-stage enterprises should focus on building knowledge absorptive capacity, mature-stage enterprises on cultivating open innovation ecosystems, and decline-stage enterprises on targeted support programs for intelligent transformation. Through such differentiated policy design, intelligent manufacturing technologies can be more widely adopted and more deeply integrated across enterprise types, ensuring that technological investment maximizes long-term competitive advantage and sustainable development.

Acknowledgments This paper is supported by the Major Project of the National Social Science Fund of China "Research on the Strategy and Policy of Domestic Substitution for Key Core Technologies in Intelligent Manufacturing" (No. 21&ZD132), and by the Dengfeng Strategy Project for the Development of Advantage Disciplines in Enterprise Management at the Chinese Academy of Social Sciences (No. DF2023YS25).

References

Adizes, I. (1990). *Corporate lifecycles: How and why corporations grow and die and what to do about it*. Prentice Hall.

Anthony, J. H., & Ramesh, K. (1992). Association between accounting performance measures and stock prices: A test of the life cycle hypothesis. *Journal of Accounting and Economics*, *15*(2/3), 203–227.

Chen, J. L., Zhao, Y. X., & Lin, S. (2021). 智能制造能促进企业创新绩效吗? [Can intelligent manufacturing improve enterprise innovation performance?]. *外国经济与管理* [Foreign Economics & Management], (9), 83–101.

Chen, S. H., & Chen, A. H. (2012). 企业生命周期划分及度量方法评析 [Review of corporate life cycle classification and measurement methods]. *财会月刊* [Finance and Accounting Monthly], (27), 77–78.

Chen, Y. B. (2017). Integrated and intelligent manufacturing: Perspectives and enablers. *Engineering*, *3*(5), 588–595.

DeAngelo, H., DeAngelo, L., & Stulz, R. M. (2006). Dividend policy and the earned/contributed capital mix: A test of the life-cycle theory. *Journal of Financial Economics*, *81*(2), 227–254.

Deng, Y., & Jiang, W. Y. (2022). 智能化转型何以激发企业创新?—基于制造业劳动力多样性的解释 [Does frontier technology promote enterprise innovation? Explanation based on labor diversity of manufacturing force]. *改革* [Reform], (9), 108–122.

Ding, H. F., Zhang, R., & Zhou, R. B. (2023). 制造业企业智能化转型及其创新效应研究—基于企业生命周期理论的视角 [Research on the intelligent transformation of manufacturing enterprises and its innovation effect: The perspective of enterprise life cycle theory]. *产业经济研究* [Industrial Economics Research], (2), 83–96.

Du, C. Z., & Wang, X. L. (2024). 智能制造对制造企业创新效率的非线性影响—基于制造业服务化的调节效应 [The nonlinear impact of intelligent manufacturing on innovation efficiency of manufacturing enterprises: The moderating effect of manufacturing servitization]. *四川大学学报(哲学社会科学版)* [Journal of Sichuan University (Philosophy and Social Science Edition)], (1), 37–51.

Duran, P., Kammerlander, N., Van Essen, M., & Zellweger, T. (2016). Doing more with less: Innovation input and output in family firms. *Academy of Management Journal*, *59*(4), 1224–1264.

Gao, W. L., & Chou, J. L. (2015). Innovation efficiency, global diversification, and firm value. *Journal of Corporate Finance*, *30*, 278–298.

Goldfarb, A., & Tucker, C. (2019). Digital marketing. In J.-P. Dubé & P. E. Rossi (Eds.), *Handbook of the economics of marketing* (1st ed., Vol. 1, pp. 259–290). Elsevier.

Gu, F. (2005). Innovation, future earnings, and market efficiency. *Journal of Accounting, Auditing & Finance*, *20*(4), 385–418.

Haire, M. (1959). *Modern organization theory*. John Wiley and Sons.

Han, X., Fu, L. Y., Lü, C. Y., & Peng, J. Z. (2023). 智藏韧显: 智能制造提升工业韧性的机理与证据 [Improving resilience with intelligent manufacturing: Mechanism and evidence for intelligent manufacturing to enhance industrial resilience]. *研究与发展管理* [R&D Management], (6), 46–59.

Haug, A., Adsbøll Wickstrøm, K., Stentoft, J., & Philipsen, K. (2023). The impact of information technology on product innovation in SMEs: The role of technological orientation. *Journal of Small Business Management*, *61*(2), 384–410.

He, B., & Bai, K. J. (2021). Digital twin-based sustainable intelligent manufacturing: A review. *Advances in Manufacturing*, *9*(1), 1–21.

Hirshleifer, D., Hsu, P.-H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, *107*(3), 632–654.

Huang, Q. H., Yu, Y. Z., & Zhang, S. L. (2019). 互联网发展与制造业生产率提升: 内在机制与中国经验 [Internet development and productivity growth in the manufacturing industry: Internal mechanism and China experiences]. *中国工业经济* [China Industrial Economics], (8), 5–23.

Jiang, T. (2022). 因果推断经验研究中的中介效应与调节效应 [Mediation and moderation effects in empirical causal inference research]. *中国工业经济* [China Industrial Economics], (5), 100–120.

Joshi, K. D., Chi, L., Datta, A., & Han, S. (2010). Changing the competitive landscape: Continuous innovation through IT-enabled knowledge capabilities. *Information Systems Research*, *21*(3), 472–495.

Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., Kim, B. H., & Noh, S. D. (2016). Smart manufacturing: Past research, present findings, and future directions. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *3*(1), 111–128.

Kodama, T. (2008). The role of intermediation and absorptive capacity in facilitating university-industry linkages—An empirical study of TAMA in Japan. *Research Policy*, *37*(8), 1224–1240.

Kusiak, A. (2023). Smart manufacturing. In S. Y. Nof (Ed.), *Springer handbook of automation* (pp. 973–985). Springer.

Li, J. X. (2020). 中国制造业智能化程度评价及其影响因素研究 [Research on evaluation benchmark and influencing factors for China's manufacturing intelligentization]. *中国软科学* [China Soft Science], (1), 154–163.

Li, R. M., & Li, X. S. (2025). 加入大企业供应链网络如何影响中小企业创新? [How does joining a large enterprise's supply chain network affect the innovation of SMEs?]. *经济与管理研究* [Research on Economics and Management], (1), 109–123.

Liang, P., Liang, L., & Qi, D. (2024). 工业机器人应用能否提升企业创新能力 [Can industrial robot applications improve the innovation ability of enterprises]. *广东财经大学学报* [Journal of Guangdong University of Finance and Economics], (2), 59–70.

Liu, J. L., & Li, J. (2024). 智能制造: 概念演化、体系解构与高质量发展 [Intelligent manufacturing: Concept evolution, system deconstruction, and high-quality development]. *改革* [Reform], (2), 75–88.

Liu, S. Y., Lin, Z. F., & Leng, Z. P. (2020). 税收激励提高企业创新水平了吗?—基于企业生命周期理论的检验 [Whether tax incentives stimulate corporate innovation: Empirical evidence based on corporate life cycle theory]. *经济研究* [Economic Research Journal], (6), 105–121.

Liu, W., Lu, H. F., Yu, L. Z., & Jiang, Y. C. (2024). 智能化转型、经济政策不确定性与制造业创新—基于创新动机视角 [Intelligent transformation, economic policy uncertainty, and manufacturing innovation: From the perspective of innovation motivation]. *广东财经大学学报* [Journal of Guangdong University of Finance & Economics], (3), 4–19.

Lui, A. K. H., Lee, M. C. M., & Ngai, E. W. T. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research*, *308*(1/2), 373–388.

Mann, K., & Püttmann, L. (2023). Benign effects of automation: New evidence from patent texts. *The Review of Economics and Statistics, 105*(3), 562–579.

Meng, F. S., & Zhao, G. (2018). 传统制造向智能制造发展影响因素研究 [Research on the influence factors of traditional manufacturing to the development of intelligent manufacturing]. *科技进步与对策* [Science & Technology Progress and Policy], (1), 66–72.

Miller, D., & Friesen, P. H. (1984). A longitudinal study of the corporate life cycle. *Management Science*, *30*(10), 1161–1183.

Müller, J. M., Buliga, O., & Voigt, K.-I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, *132*, 2–17.

Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *American Economic Review*, *104*(6), 1630–1666.

Pan, L. Q., Li, J., & Yu, M. L. (2024). 人工智能如何影响劳动力需求和结构?—基于上市公司年报数据的实证检验 [How does artificial intelligence affect labor demand and structure? An empirical test based on annual report data of listed companies]. *经济与管理研究* [Research on Economics and Management], (10), 77–98.

Pei, J., Zhou, Y., Peng, Z. L., & Yang. S. L. (2023). 高端装备智能制造创新运作: 从平台型企业到平台型供应链 [Innovative operations of intelligent manufacturing in high-end equipment: From platform enterprises to platform supply chains]. *管理世界* [Journal of Management World], (1), 226–240.

Qi, W. H., Li, B., & Qiu, Y. (2023). 服务业开放阻碍制造业就业了吗: 基于行业异质性的视角 [Has the opening of the service sector hindered manufacturing employment: A perspective based on industry heterogeneity]. *中国软科学* [China Soft Science], (12), 38–48.

Quan, X. F., & Li, C. (2022). 智能制造与成本粘性—来自中国智能制造示范项目的准自然实验 [Cost stickiness mitigation effect of intelligent manufacturing: On a quasi-natural experiment of Chinese intelligent manufacturing demonstration project]. *经济研究* [Economic Research Journal], (4), 68–84.

Ravichandran, T., Han, S., & Mithas, S. (2017). Mitigating diminishing returns to R&D: The role of information technology in innovation. *Information Systems Research*, *28*(4), 812–827.

Shen, Y., & Zhang, X. W. (2022). 智能制造、产业集聚与劳动力错配 [Intelligent manufacturing, industrial agglomeration, and labor misallocation]. *中国流通经济* [China Business and Market], (4), 89–100.

Song, X. G., & Du, J. H. (2021). 智能制造如何影响劳动收入份额—基于中国省级面板数据的实证研究 [How does intelligent manufacturing affect the labor income share—An empirical study based on provincial panel data in China]. *经济理论与经济管理* [Economic Theory and Business Management], (11), 79–96.

Wang, J., Lu, Y., Fan, S., Hu, P., & Wang, B. (2022). How to survive in the age of artificial intelligence? Exploring the intelligent transformations of SMEs in central China. *International Journal of Emerging Markets*, *17*(4), 1143–1162.

Wang, X. Y., & Qin, J. Y. (2023). 创新竞争与企业高质量创新模式选择—来自专利被无效宣告的经验证据 [Innovation competition and the choice of high-quality innovation strategy: Empirical evidence from patent invalidation]. *经济研究* [Economic Research Journal], (11), 80–98.

Wang, Y. Q., & Dong, W. (2020). 机器人的兴起如何影响中国劳动力市场?—来自制造业上市公司的证据 [How the rise of robots has affected China's labor market: Evidence from China's listed manufacturing firms]. *经济研究* [Economic Research Journal], (10), 159–175.

Wei, L., Wang, Y. L., Zhang, X., & Zhao, Z. (2024). 数字化转型提升企业创新效率的网络机制—合作和知识双重创新网络结构洞的中介作用 [Network mechanisms for digital transformation to improve enterprise innovation efficiency: The mediating role of cooperation and knowledge dual innovation network structural holes]. *西部论坛* [West Forum], (1), 81–95.

Wen, S. B., Zhang, J. Q., & Jiao, R. (2022). 智能制造、市场化程度与企业运营效率—基于A股制造业上市公司年报的文本分析 [Smart manufacturing, marketization, and enterprise operating efficiency: A text analysis based on annual reports of A-share listed manufacturing enterprises]. *会计研究* [Accounting Research], (11), 102–117.

Wu, F., Hu, H. Z., Lin, H. Y., & Ten, X. Y. (2021). 企业数字化转型与资本市场表现—来自股票流动性的经验证据 [Corporate digital transformation and capital market performance: Empirical evidence from stock liquidity]. *管理世界* [Journal of Management World], (7), 130–144.

Wu, J., & Ji, X. Y. (2024). 数字经济发展与企业协同创新—基于创新链升级与供应链优化视角 [Digital economy development and enterprise collaborative innovation—From the perspectives of innovation chain upgrading and supply chain optimization]. *首都经济贸易大学学报* [Journal of Capital University of Economics and Business], (2), 3–18.

Wu, Q., Han, T. R., Du, Y. Y., & Li, M. X. (2025). 数字技术赋能平台创新生态系统韧性提升研究 [Digital technologies empowering resilience enhancement of platform innovation ecosystems]. *经济与管理研究* [Research on Economics and Management], (3), 112–127.

Wu, X. J., Ma, M. T., & Wang, X. Q. (2023). 智能制造研究述评 [A literature review on intelligent manufacturing]. *研究与发展管理* [R&D Management], (6), 32–45.

Xi, J. P. (2022). *高举中国特色社会主义伟大旗帜　为全面建设社会主义现代化国家而团结奋斗—在中国共产党第二十次全国代表大会上的报告(2022年10月16日)* [Hold high the great banner of socialism with Chinese characteristics and strive in unity to build a modern socialist country in all respects—Report to the 20th National Congress of the Communist Party of China (October 16, 2022)]. 人民出版社 [People's Publishing House].

Xiao, J. H., & Li, W. T. (2020). 智能制造对企业战略变革与创新的影响—资源基础变革视角的探析 [The impact of smart manufacturing on enterprises' strategic change and innovation: An exploration from a resource-based change perspective]. *财经问题研究* [Research on Financial and Economic Issues], (2), 38–46.

Xiao, W., & Lin, G. (2014). 政府支持、研发管理与技术创新效率—基于中国工业行业的实证分析 [Government support, R&D management, and technological innovation efficiency: An empirical analysis based on China's industrial sectors]. *管理世界* [Journal of Management World], (4), 71–80.

Xie, X. M., & Zuo, L. L. (2013). 企业协同创新网络特征与创新绩效：基于知识吸收能力的中介效应研究 [Characteristics of collaborative innovation networks and innovation performance of electronic information firms: The mediating effect of knowledge absorptive capacity]. *南开管理评论* [Nankai Business Review], (3), 47–56.

Yang, H. C., Luo, Y. C., & Li, L. S. (2024). 智能制造对制造业高质量发展的影响研究—基于"量"与"质"的视角 [The impact of smart manufacturing on high-quality development of manufacturing: From the perspectives of "quantity" and "quality"]. *科学学研究* [Studies in Science of Science], (8), 1644–1655.

Yang, Q. F. (2013). 高技术产业地区研发创新效率的决定因素—基于随机前沿模型的实证分析 [Research on the influencing factors of R&D innovation efficiency of high-tech industries: An empirical analysis based on the stochastic frontier model]. *管理评论* [Management Review], (6), 47–58.

Yang, S. L., Wang, J. M., Shi, L. Y., Tan, Y. J., & Qiao, F. (2023). 新一代信息技术环境下高端装备智能制造工程管理理论与方法 [Engineering management theories and methods for intelligent manufacturing of high-end equipment under the new-generation information technology environment]. *管理世界* [Journal of Management World], (1), 177–190.

Yao, J. Q., Zhang, H. P., Guo, L. P., & Feng, X. (2024). 人工智能如何提升企业生产效率?—基于劳动力技能结构调整的视角 [How does artificial intelligence improve enterprise productivity? From the perspective of labor skill-structure adjustment]. *管理世界* [Journal of Management World], (2), 101–116.

Yin, H. Y., & Li, C. (2022). 智能制造赋能企业创新了吗?—基于中国智能制造试点项目的准自然试验 [Can intelligent manufacturing empower enterprise innovation? A quasi-natural experiment based on China's intelligent manufacturing demonstration project]. *金融研究* [Journal of Financial Research], (10), 98–116.

Yu, F. F., Wang, L. T., & Li, X. T. (2020). The effects of government subsidies on new energy vehicle enterprises: The moderating role of intelligent transformation. *Energy Policy*, *141*, 111463.

Yu, L. Z., Wei, X. H., Sun, Z. W., & Wu, C. X. (2021). 工业机器人、工作任务与非常规能力溢价—来自制造业"企业–工人"匹配调查的证据 [Industrial robots, work tasks, and non-routine skill premiums: Evidence from an "enterprise–worker" matched survey in manufacturing]. *管理世界* [Journal of Management World], (1), 47–59.

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy*

of Management Review, *27*(2), 185–203.

Zeng, J. L., & Zhou, J. (2024). 智能制造促进了企业融通创新吗? [Does intelligent manufacturing promote business co-innovation?]. *首都经济贸易大学学报* [Journal of Capital University of Economics and Business], (6), 79–93.

Zhang, Q., Zhao, S. Y., & Cai, Z. Y. (2023). 高端装备智能制造价值链的生产自组织与协同管理: 设计制造一体化协同研发实践 [Production self-organization and collaborative management of the value chain of intelligent manufacturing in high-end equipment: Integrated design–manufacturing collaborative R&D practice]. *管理世界* [Journal of Management World], (3), 127–140.

Zhang, S. S., Hu, H. G., Sun, L., & Zhang, L. (2021). 智能制造如何影响企业绩效?—基于"智能制造试点示范专项行动"的准自然实验 [How does intelligent manufacturing affect enterprise performance? Quasi-natural experiment based on "special action for pilot demonstration of intelligent manufacturing"]. *科学学与科学技术管理* [Science of Science and Management of S. & T.], (11), 120–136.

Zhang, Y. F., Zhang, G., Wang, J. Q., & Sun, S. D. (2015). Real-time information capturing and integration framework of the internet of manufacturing things. *International Journal of Computer Integrated Manufacturing*, *28*(8), 811–822.

Zheng, P., Wang, H. H., Sang, Z. Q., & Zhong, R. Y. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering*, *13*(2), 137–150.

Zhou, J., Li, P., Zhou, Y., Wang, B., Zang, J., & Liu, M. (2018). Toward new-generation intelligent manufacturing. *Engineering*, *4*(1), 11–20.

Zhou, S. J., & Shan, F. X. (2023). Discovery of innovation effect and spillover effect: Evidence from intelligent manufacturing promoting low-carbon development. *Journal of Innovation & Knowledge*, *8*(3), 100383.

Zhou, X. S., Chen, C., & Du, M. (2016). 融资需求、企业生命周期与盈余管理—基于非金融行业A股的经验证据 [Financing demand, enterprise life cycle and earnings management: Empirical evidence based on A-listed non-financial companies]. *山西财经大学学报* [Journal of Shanxi University of Finance and Economics], (9), 25–38.