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Research on the Impact of Artificial Intelligence on the High-Quality Development of Manufacturing

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Abstract: A comprehensive evaluation system encompassing five dimensions is constructed in this paper using panel data from 30 Chinese provinces spanning 2012 to 2023. This system serves as the basis for examining whether artificial intelligence can empower the high-quality development of China's manufacturing sector. R&D capability, green development, openness, economic efficiency, and industrial coordination. Employing the two-way fixed effects model, instrumental variable method, mediation effect model, and heterogeneity tests, the study finds that AI significantly promotes the high-quality development of manufacturing. This conclusion remains robust after addressing endogeneity. AI drives manufacturing development through two pathways: promoting technological innovation and optimizing human capital structure. The empowering effect exhibits significant heterogeneity, with the strongest effect in the eastern region. The effect is significant in coastal areas but not in inland areas, and regions with weak digital infrastructure show higher marginal returns. Based on these findings, this paper proposes differentiated regional AI development strategies, a technology-talent collaborative support system, and coordinated advancement of new digital infrastructure to facilitate the transformation of China's manufacturing industry from a manufacturing giant to a manufacturing powerhouse.

Keywords: Artificial Intelligence; Manufacturing; High-Quality Development; Technological Innovation; Human Capital

1. Introduction

Following the reform and opening-up, China has quickly risen to become both the world's largest manufacturing nation and the second-largest economy globally. However, with profound changes in both domestic and international development environments, China’s economy has entered a new stage of high-quality development. As the mainstay of the national economy, the manufacturing sector serves as the foundation of national prosperity and security. Its quality improvement directly affects industrial competitiveness and sustained economic growth. Whether AI can effectively empower and systematically drive China’s manufacturing industry to achieve a leap from quantity to quality has become a critical issue concerning national competitiveness and global value chain positioning.

The application of AI in manufacturing has attracted increasing attention from scholars. Existing studies have explored AI’s impact on employment scale, labor structure, and economic growth. Some studies have also investigated the relationship between AI and manufacturing development, focusing on innovation performance, green transformation, and global value chain upgrading. However, the existing literature has several limitations.

First, most studies approach the topic from a single dimension, lacking an integrated analytical framework that places AI within the multi-dimensional, systematic goal of high-quality manufacturing development. Second, while some studies identify potential mediating paths such as technological innovation and human capital structure, few systematically test these mechanisms within a unified framework, leaving the black box of AI’s empowering effect largely unopened. Third, existing heterogeneity analyses are often limited to simple regional groupings, with insufficient attention to how boundary conditions such as digital infrastructure and regional endowments moderate AI’s empowering effect. Fourth, the potential endogeneity between AI and manufacturing development has not been adequately addressed in many studies, which may affect the reliability of causal inference.

This study makes three main contributions. First, it constructs a comprehensive evaluation system that reflects the multi-dimensional nature of high-quality manufacturing development. Second, it empirically tests the dual mediating pathways of technological innovation and human capital structure, revealing the internal logic of AI's empowering effect. Third, it conducts multi-dimensional heterogeneity analysis, including regional, coastal-inland, and digital infrastructure levels, providing refined empirical evidence for differentiated policy formulation.

2. Literature Review

Acemoglu and Restrepo found that increasing robot density significantly reduces local employment and wages, while Chen et al. showed that industrial robots suppress the inflow of low-skilled migrant workers. [1] However, Graetz and Michaels found that robots do not significantly reduce overall employment and may promote job growth in some industries. [2] Autor argued that automation reduces production costs and stimulates demand, creating compensating employment effects in the long run. Regarding labor structure, Goos found that robot adoption widens wage gaps and polarizes labor structures, while Yao et al. showed that AI increases demand for high-skilled workers in Chinese manufacturing firms. [3] The second area examines the role of AI in economic growth and global value chains. Zeira proposed that automation improves productivity through capital deepening. [4] Lyu et al. and Liu and Pan demonstrated that AI promotes firms' participation in global value chains and improves their position in the division of labor. [5] The third area concerns the measurement and driving factors of manufacturing high-quality development. Liu and Lin proposed a five-dimension evaluation system covering innovation, industrial foundation, structural optimization, efficiency, and transformation. [6] Chao et al. constructed an evaluation logic based on the full life cycle of R&D, production, and market matching. Romer emphasized that knowledge accumulation and human capital are sources of long-term growth. Shan et al. found that intellectual property protection promotes manufacturing development through innovation incentives. [7] Yang and Zheng argued that optimizing human capital structure is more effective than simply expanding its quantity. [8] More recent studies have examined AI's multidimensional impact on manufacturing innovation, productivity, green transformation, and value chain upgrading. He and Xiong and Huang et al. found that AI deployment significantly improves innovation performance and total factor productivity. Zhu and Wang found that AI promotes green innovation through cost-saving and knowledge spillover effects. [9] Liu and Han found that AI enhances manufacturing resilience and green competitiveness. Yang and Lu demonstrated that AI supports manufacturing development through technological innovation and human capital optimization. Zhang et al. found that China's large domestic market amplifies AI's positive effect on export product quality. [10] Despite these valuable contributions, existing research lacks an integrated framework connecting AI to the mediating mechanisms of technological innovation and human capital have not been systematically tested, leaving the black box of AI's empowering effect largely unopened.

3. Measurement of Manufacturing High-Quality Development

Table 1 presents the evaluation system used to assess the high-quality development of manufacturing.

To standardize the positive and negative indicators within the manufacturing high-quality development evaluation system, this study applies the range method. This eliminates differences in the dimensions and magnitudes of the raw data, ensuring that each indicator can truly reflect its own characteristics and contribution in the comprehensive measurement process.

The formula for standardizing positive indicators is as follows:

$$X_{ij}=\frac{x_{ij}\text{-}\min(x_{1j},x_{2j},\ldots x_{nj})}{\max(x_{1j},x_{2j},\ldots x_{nj})\text{-}\min(x_{1j},x_{2j},\ldots x_{nj})} \quad (1)$$

The formula for standardizing negative indicators is as follows:

$$X_{ij}=\frac{\min(x_{1j},x_{2j},\ldots x_{nj})\text{-}x_{ij}}{\max(x_{1j},x_{2j},\ldots x_{nj})\text{-}\min(x_{1j},x_{2j},\ldots x_{nj})} \quad (2)$$

Second, based on the evaluation indicator system constructed above, to fully reflect the differences in the high-quality development level of manufacturing across 30 provinces in China, a basic data matrix containing 30 provincial evaluation units and 15 secondary indicators is established. On this basis, the information entropy value of each indicator is calculated.

$$E_j = \ln\frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_{ij}}{\sum_{i=1}^{n}X_{ij}}\ln\frac{X_{ij}}{\sum_{i=1}^{n}X_{ij}}\right) \quad (3)$$

Third, based on the information entropy results calculated in the second step, the weight coefficients corresponding to each secondary indicator in the manufacturing high-quality development evaluation system are further calculated.

$$W_j = (1-E_j)/\sum_{j=1}^{m}(1-E_j) \quad (4)$$

Fourth, using the linear weighted summation method, the manufacturing high-quality development index for each province in China is comprehensively calculated and quantitatively evaluated.

$$S_i = \sum_{j=1}^{m} W_j \times X_{ij} \quad (5)$$

Table 1. Evaluation System for Manufacturing High-Quality Development

Dimension	Indicator	Measurement
R&D Capability	R&D Input Intensity	R&D expenditure of industrial enterprises above designated size / GDP
	Patents per Capita	Number of invention patents / R&D personnel
	R&D Personnel Intensity	R&D personnel / manufacturing employment
Green Development	Energy Consumption per Unit of Value Added	Coal consumption / industrial value added
	SO_2 Emission per Unit of Value Added	SO_2 emissions / industrial value added
	Solid Waste Generation per Unit of Value Added	Industrial solid waste / industrial value added
	COD Emission per Unit of Value Added	Chemical oxygen demand / industrial value added
Openness	Trade Openness	Total imports and exports / GDP
	FDI Openness	Foreign direct investment / GDP
Economic Efficiency	Manufacturing Growth Rate	Current year industrial value added / previous year
	Profit Margin of Manufacturing Enterprises	Total profit of industrial enterprises above designated size / total cost of main business
	Labor Productivity in Manufacturing	Industrial value added / average employment in manufacturing
Industrial Coordination	Share of Manufacturing Output	Industrial value added / GDP
	Industrial Structure Upgrading	High-tech industry revenue / industrial revenue of enterprises above designated size
	Share of Tertiary Industry Value Added	Tertiary industry value added / secondary industry value added

4. Research Hypotheses

Based on the theoretical framework of techno-economic paradigm, endogenous growth theory, and new structural economics, this study proposes three hypotheses.

First, as a new generation of general-purpose technology, AI possesses characteristics such as substitutability, penetration, and creativity. These features enable AI to improve the contribution rate of production factors and optimize resource allocation efficiency, thereby systematically driving manufacturing transformation in efficiency, quality, and growth drivers. Accordingly, this study proposes:

Hypothesis 1 (H1): AI has a positive promoting effect on the high-quality development of manufacturing.

Second, AI can reshape the innovation behavior of manufacturing firms and expand the boundaries of independent technology R&D. By accelerating knowledge spillover and improving R&D efficiency, AI enhances technological innovation capability, which in turn promotes high-quality manufacturing development. Accordingly, this study proposes:

Hypothesis 2 (H2): AI promotes the high-quality development of manufacturing by enhancing technological innovation.

Third, the application of AI is reshaping labor market demand. While substituting routine and repetitive labor, AI creates new demand for high-skilled and interdisciplinary talents. This forces an upward shift in the labor force structure, optimizing human capital allocation. Accordingly, this study proposes:

Hypothesis 3 (H3): AI promotes the high-quality development of manufacturing by optimizing human capital structure.

5. Variable Selection

5.1 Dependent Variable

The dependent variable is the manufacturing high-quality development index (High). This index is calculated using the entropy method based on the five-dimensional evaluation system constructed in Section 3, covering R&D capability, green development, openness, economic efficiency, and industrial coordination.

5.2 Independent Variable

The independent variable is the industrial robot penetration rate (AI), which serves as the core proxy indicator for AI development level. Following Acemoglu and Restrepo and Wang and Dong, this study constructs a provincial-level industrial robot penetration rate based on the Bartik instrumental variable approach. The data are sourced from the International Federation of Robotics (IFR). The calculation formula is as follows:

$$AI_{jt}=\sum_{j=1}^{J}\frac{Labor_{\mathrm{ijt}}}{Labor_{\mathrm{it}}}\times\frac{Robot_{jt}}{Labor_{\mathrm{jt}}} \quad (6)$$

where $\mathrm{Robot_{jt}}$ represents the stock of industrial robots installed in industry j in year t, $\mathrm{Labor_{jt}}$ represents employment in industry j in year t, $\mathrm{Labor_{jt}}$ represents employment in province i in year t, and $\mathrm{Labor_{ijt}}$ represents employment in industry j in province i in year t.

5.3 Control Variables

To isolate the net effect of AI on manufacturing high-quality development, this study controls for urbanization level, social consumption level, government intervention, economic development level, and financial development level.

5.4 Mediating Variables

To test the proposed mechanisms, this study selects two mediating variables:

(1) Technological innovation (tech), measured by the ratio of science and technology expenditure to local general public budget expenditure. This reflects the government's support for technological innovation.

(2) Human capital structure (human), measured by average years of schooling per capita, following Liu and Gong. The calculation formula is:

$$\mathrm{Human}=(\mathrm{Primary}\times 6+\mathrm{Junior}\times 9+\mathrm{Senior}\times 12+\mathrm{College}\times 16)/\mathrm{Total\ population\ aged\ 6\ and\ above} \quad (8)$$

This indicator reflects the overall quality of the regional labor force.

6. Model Specification

6.1 Benchmark Regression Model

To examine the direct impact of AI on manufacturing high-quality development, this study specifies a two-way fixed effects model as the benchmark regression framework:

$$ln\,(high)_{it}=\beta_0+\beta_1 ai_{it}+\textstyle\sum_{k=1}^{K}\gamma_k\,Controls_{it}^{k}+\mu_i+\lambda_t+\varepsilon_{it} \quad (9)$$

where $\ln(\mathrm{high})_{\mathrm{it}}$ is the logarithm of the manufacturing high-quality development index for province i in year t, $\mathrm{ai_{it}}$ is the core explanatory variable representing the level of AI development, $\mathrm{Controls_{it}^{k}}$ represents a set of control variables including urbanization level (lncity), social consumption level (lncon), government intervention (lngov), economic development level (lngdp), and financial development level (lnfin). μ_i denotes province fixed effects, controlling for time-invariant regional heterogeneity. λ_t denotes year fixed effects, controlling for time trends. ε_{it} is the random error term. The coefficient β_1 is the core estimate of interest. If β_1 is significantly positive, it indicates that AI has a positive promoting effect on manufacturing high-quality development.

6.2 Mechanism Analysis Model

This approach proceeds in three steps. First, it establishes that the core explanatory variable has a significant effect on the outcome variable. Second, it examines the effect of the core explanatory variable on the mediating variables. Third, relying on established literature and theoretical frameworks, it provides a theoretical explanation for how the mediating variables influence the outcome variable.

The model for testing the impact of AI on mediating variables is specified as follows:

$$\ln(\mathrm{high})_{\mathrm{it}}=\beta_0+\beta_1\mathrm{ai_{it}}+\sum_{k=1}^{K}\gamma_k\,\mathrm{Controls_{it}^{k}}+\mu_i+\lambda_t+\varepsilon_{it} \quad (10)$$

Where $\mathrm{M_{it}}$ represents the mediating variable. This study focuses on two pathways: technological innovation (tech), measured by the ratio of science and technology expenditure to local fiscal expenditure, and human capital structure (human), measured by average years of schooling per capita.

If α_1 in the above model is significant, it indicates that AI has a significant impact on the mediating variable, satisfying the first step of the mechanism test. Based on this, combined with existing literature and theory, this study demonstrates the impact of the mediating variable on manufacturing high-quality development, thereby jointly explaining the complete pathway through which AI affects manufacturing high-quality development via this mechanism. This approach avoids the multicollinearity and identification bias problems that may arise from the traditional three-step method, enhancing the robustness and reliability of the mechanism analysis.

7. Empirical Analysis

7.1 Benchmark Regression

Table 2 reports the benchmark regression results. Column (1) includes only province fixed effects, showing a coefficient of 1.1322 for AI, significant at the 1% level. Column (2) adds control variables, and the coefficient becomes 0.4689, still significant at 1%. Column (3) further includes year fixed effects, and the coefficient is 0.5357, significant at 1%. Hypothesis 1 is therefore supported, as the findings consistently demonstrate a significant positive relationship between artificial intelligence and the high-quality development of manufacturing.

Table 2. Benchmark Regression Results

	(1) Model(1)	(2) Model(2)	(3) Model(3)
ai	1.1322***	0.4689***	0.5357***
	(14.1784)	(2.7620)	(2.8379)
lncity		0.0711	0.2255
		(0.2911)	(0.7278)
lncon		-0.2560***	-0.2669***
		(-3.0411)	(-3.1296)
lngdp		0.4135***	0.5129***
		(3.7058)	(3.0938)
lngov		0.1154	0.1046
		(1.5631)	(1.3943)
lnfin		-0.1594**	-0.1546**
		(-2.1315)	(-2.0599)
cons	-2.3874	-2.7162	-2.7637
	(-134.68)	(-8.7324)	(-8.7312)
Individual fixed effects	Yes	Yes	Yes
Year fixed effects	No	No	Yes
N	360	360	360
adj. R^2	0.3314	0.3991	0.3985

7.2 Endogeneity Test

The first-stage regression shows a significant positive correlation between cable density and AI. The Anderson canonical correlation LM statistic is 31.46 (p=0.0000), rejecting the null of under-identification. The Cragg-Donald Wald F statistic is 34.25, exceeding the Stock-Yogo critical value of 16.38, rejecting weak instruments. The second-stage results show that the coefficient of AI remains significantly positive at 0.3227 ($p<0.01$), confirming the robustness of the causal relationship. As shown in Table 3.

7.3 Robustness Tests

This study conducts two robustness tests. First, after winsorizing all continuous variables at the 5% level, the coefficient for artificial intelligence retains a value of 0.4689 and maintains statistical significance at the 1% level. Second, replacing the core explanatory variable with an alternative AI development index (ai2) yields a coefficient of 0.1594, also significant at 1%. Table 4 indicate that the benchmark findings are not driven by outliers or specific measurement methods.

Table 3. Instrumental Variable Endogeneity Test Results

VARIABLES	(1) first stage	(2) second stage
cable	0.0047***	
	(5.8524)	
ai		0.3227***
		(5.0884)
lncity	-0.4383*	-0.2464***
	(-1.8012)	(-3.4591)
lncon	0.1200	-0.1042***
	(1.5248)	(-3.6338)
lngdp	0.0313***	0.0037
	(7.2272)	(1.4254)
lngov	-1.0384***	0.3207**
	(-4.1298)	(2.5590)
lnfin	0.0232**	-0.0143***
	(2.3971)	(-3.5585)
_cons	0.1355	0.2131
	(1.1914)	(2.3523)
N	360	360
adj. R^2	0.7010	0.4969

Table 4. Results of Robustness Checks

	(1) Winsor 5%	(2) Replace AI2
ai	0.4689***	
	(2.7620)	

ai2		0.1594***
		(3.5068)
lncity	0.0711	-0.2827
	(0.2911)	(-1.1623)
lncon	-0.2560***	-0.2178***
	(-3.0411)	(-2.6871)
lngdp	0.4135***	0.4262***
	(3.7058)	(4.4047)
lngov	0.1154	0.0340
	(1.5631)	(0.4755)
lnfin	-0.1594**	-0.0922
	(-2.1315)	(-1.2106)
_cons	-2.7162***	-3.3981***
	(-8.7325)	(-13.0146)
N	360	360
R^2	0.458	0.463
adj. R^2	0.399	0.405

7.4 Heterogeneity Tests

Regional heterogeneity. The sample is divided into eastern, central, and western regions. The AI coefficients are 0.5466 (eastern), 0.3597 (central), and 0.2783 (western), all statistically significant. This gradient pattern reflects the eastern region's advantages in innovation resources and digital infrastructure. As shown in Table 5.

Digital infrastructure heterogeneity. Using the median internet penetration rate as the threshold, the AI coefficient is 1.4478 in low digital infrastructure regions and 0.6388 in high digital infrastructure regions. This reveals a pattern of higher marginal returns in regions with weaker digital infrastructure, indicating catch-up potential. As shown in Table 6.

Table 5. Regional Heterogeneity Test Results

	(1) Eastern region	(2) Central region	(3) Western region
ai	0.5466***	0.3597**	0.2783**
	(3.2212)	(2.4343)	(2.4860)
lncity	0.1142	-1.5108	-1.8904***
	(0.4252)	(-1.3624)	(-3.4596)
lncon	-0.3017***	-0.1935	0.0047
	(-3.2207)	(-1.3417)	(0.0284)
lngdp	0.1103	0.8141***	0.9174***
	(0.9948)	(2.7852)	(4.3532)
lngov	-0.0300	-0.4643**	0.1265
	(-0.3498)	(-2.1347)	(1.1071)
lnfin	0.0714	-0.7608***	0.0647
	(1.0091)	(-4.1123)	(0.3861)
_cons	-2.3487***	-6.0937***	-5.3219***
	(-8.7327)	(-5.6993)	(-7.3862)
N	132	96	132
R^2	0.621	0.554	0.517
adj. R^2	0.569	0.484	0.450

Table 6. Heterogeneity Test Based on Digital Infrastructure Level

	(1)	(2)
	High digital infrastructure regions	Low digital infrastructure regions
ai	0.6388***	1.4478***
	(3.5762)	(3.5783)
lncity	0.2623	-1.7563***
	(0.8621)	(-3.9196)
lncon	-0.2005*	-0.0635
	(-1.7950)	(-0.5364)
lngdp	0.0698	0.7725***
	(0.5952)	(4.1138)
lngov	-0.1311	0.2812***
	(-1.4656)	(2.6727)
lnfin	0.0092	-0.0958
	(0.1120)	(-0.7603)
_cons	-2.4736***	-4.5045***
	(-8.0431)	(-7.3859)
N	180	180
R^2	0.528	0.508
adj. R^2	0.454	0.429

7.5 Mechanism Tests

Following Jiang, this study tests two mediating pathways. Column (1) of Table 3 shows the benchmark regression. Column (2) shows that AI has a significant positive effect on technological innovation (coefficient 0.0412, $p<0.05$). Column (3) shows that AI has a significant positive effect on human capital structure (coefficient 0.0137, $p<0.01$). Combined with existing literature confirming that both technological innovation and human capital structure promote manufacturing high-quality development, these results support Hypotheses 2 and 3. As shown in Table 7.

Table 7. Mediation Mechanism Test Results

	(1)	(2)	(3)
	Benchmark	Technological Innovation	Human Capital
ai	0.1708***	0.0412**	0.0137***
	(6.4091)	(2.1367)	(2.6437)
lncity	-0.1673***	0.1582***	0.0302
	(-3.8235)	(5.0005)	(1.1586)
lncon	-0.0332***	0.0283***	-0.0032
	(-2.7558)	(3.2508)	(-0.4180)
lngdp	0.0138	0.0093	0.0249
	(0.5907)	(0.5511)	(1.5866)
lngov	0.0258**	0.0350***	-0.0123*
	(2.4343)	(4.5697)	(-1.7215)
lnfin	-0.0280***	-0.0303***	-0.0130*
	(-2.6375)	(-3.9587)	(-1.7753)
year_id	0.0050**	0.0036**	0.0046***
	(2.1242)	(2.0893)	(2.6350)

_cons	0.0267	2.7887***	2.1311***
	(0.5967)	(86.2434)	(71.1930)
N	360	360	360
R^2	0.573	0.754	0.794
adj. R^2	0.525	0.726	0.771

8. Main Conclusions

Drawing on panel data from 30 Chinese provinces observed between 2012 and 2023, this study applies a range of econometric techniques—namely the two-way fixed effects model, the instrumental variable method, the mediation effect model, and heterogeneity tests—to systematically investigate how artificial intelligence influences the high-quality development of China's manufacturing industry, including its impact, transmission mechanisms, and boundary conditions. The main conclusions derived from this analysis are presented as follows.

The first conclusion is that artificial intelligence exerts a promoting effect on the high-quality development of manufacturing, which is both statistically significant and empirically robust. The benchmark regression results show that a one-unit increase in the AI development level leads to a 0.5357-unit increase in the manufacturing high-quality development index, significant at the 1% level.

Second, AI promotes manufacturing high-quality development through two pathways: promoting regional technological innovation and optimizing human capital structure. The mediation effect test shows that AI's coefficient on technological innovation is 0.0412 ($p<0.05$), and its coefficient on human capital structure is 0.0137 ($p<0.01$). These two pathways form a synergistic closed loop, jointly constituting the dual-drive engine of technology and talent.

Third, the empowering effect of AI exhibits significant heterogeneity. The promotion effect follows a gradient pattern: strongest in the eastern region (coefficient 0.5466), followed by the central (0.3597) and western (0.2783) regions. The effect is significantly positive in coastal areas but insignificant in inland areas, indicating constraints from technological absorption capacity and industrial supporting facilities. Notably, regions with weaker digital infrastructure show higher marginal returns (coefficient 1.4478 vs. 0.6388), revealing a pattern of high returns from low starting points.

9. Policy Implications

The empirical evidence presented above leads this study to offer several policy recommendations, which are organized as follows.

Coordinating digital infrastructure layout to solidify the foundation of technology empowerment. Given the higher marginal returns in regions with weak digital infrastructure, the government should accelerate the layout of 5G networks, industrial internet nodes, and regional computing centers in central and western regions. Eastern regions should focus on core algorithm research and development, high-end industrial software, and intelligent sensing chips, creating globally influential intelligent manufacturing innovation hubs.

Building a technology-talent collaborative support system. Since AI promotes manufacturing development through both technological innovation and human capital optimization, the government should establish collaborative innovation alliances led by leading enterprises, universities, and research institutes. It should also reform higher education and vocational training systems to cultivate interdisciplinary engineers and high-skilled talents, while implementing digital skills training programs for existing workers.

Implementing gradient regional strategies to promote east-central-west coordination. Given the significant regional heterogeneity, eastern regions should focus on original innovation and industrial ecosystem construction. Central regions should concentrate on introducing, digesting, and re-innovating mature intelligent technologies. Western regions should combine local resource endowments to promote AI applications in smart energy, green mining, and specialty agricultural product processing.

Fostering a green-intelligent integrated industrial ecosystem to cultivate world-class advanced manufacturing clusters. The government should promote deep integration of AI and green manufacturing technologies, enabling real-time monitoring, intelligent scheduling, and optimization of energy consumption and emissions. It should also encourage enterprises to develop new business models such as remote maintenance, predictive maintenance, personalized customization, and shared manufacturing, transforming from product providers to comprehensive solution service providers.

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