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Intelligent Manufacturing will Affect Enterprises Carbon Emission Intensity

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Reducing carbon emissions is a common global goal, impacting not only climate change but also various industries. Many countries worldwide have implemented policies and measures to reduce carbon emissions, employing industrial transformation and upgrading or emerging technologies to better achieve their carbon reduction targets. Manufacturing has consistently been a high-carbon-emission sector, and the effectiveness of manufacturing enterprises in reducing emissions directly affects a country's carbon reduction goals. Therefore, this paper proposes the hypothesis that intelligent manufacturing can reduce corporate carbon intensity and verifies this hypothesis through empirical research.

1. Introduction

Facing global climate change and international environmental pressures, China, as the world’s largest developing country and a major greenhouse gas emitter, has proposed the “dual carbon goals”: peaking carbon emissions by 2030 and achieving carbon neutrality by 2060. These goals demonstrate China’s determination to tackle climate change, pursue low-carbon development, and guide industrial restructuring and economic transformation. The manufacturing industry, as the largest source of carbon emissions, is crucial for achieving these targets. In 2022, it contributed 27.7% of China’s GDP and has been the world’s largest manufacturing sector for 13 consecutive years (Guo Chaoxian, 2021). Identifying key levers for low-carbon transformation, exploring emission reduction pathways aligned with industrial growth, and implementing targeted policies are therefore essential for promoting the green transformation and high-quality development of China’s manufacturing sector.

2. Literature review

For companies aiming to reduce carbon emissions, integrating intelligent manufacturing into sustainability strategies is essential. Implementing a circular economy that emphasizes resource recycling and waste reduction can lower the carbon footprint by 15–30% compared to traditional methods (Kazakova & Lee, 2022). Digital platforms further support these efforts by enabling real-time data sharing and collaborative decision-making among stakeholders, which is critical for effective sustainability management (Ghaithan, Alshammakhi, Mohammed, & Mazher, 2023). The literature indicates that Intelligent Manufacturing technologies, including the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, are increasingly recognized for their potential to reduce corporate carbon intensity. However, existing research largely focuses on the regional or industry level, lacking in-depth analysis of the impact of Intelligent Manufacturing at the individual manufacturing enterprise level. However, micro-enterprises are both the implementers of Intelligent Manufacturing transformation and the direct sources of carbon emissions; therefore, research at the micro-enterprise level is crucial for a deeper understanding of the environmental effects of Intelligent Manufacturing. Due to limited micro-level data, most existing studies focus on regional or industry levels. Nevertheless, the optimization effects of intelligent manufacturing on enterprises suggest that it may serve as an important driver of corporate carbon reduction.Therefore, this paper hypothesizes that an increase in the level of intelligent manufacturing in enterprises will reduce carbon emission intensity.

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3. Research Design

3.1 Data sources

Currently, empirical research on the relationship between intelligent manufacturing and carbon emissions in my country mainly focuses on the macro level (Jiang et al., 2022; Liu et al., 2024a; Tian et al., 2024; Wang et al., 2024b; Yu et al., 2023a). The relative scarcity of micro-level research on this topic is primarily due to the difficulty in obtaining enterprise-level carbon emission data. Current research involving enterprise carbon emission data mainly focuses on listed companies and industrial enterprises. However, data from both types of enterprises has certain limitations. For listed companies, most studies employ estimation methods, using the proportion of the company's main business costs to the main business costs of its industry as a weight, multiplied by the carbon emissions of the industry to estimate enterprise-level carbon emissions (Liu et al., 2024b; Shang et al., 2023). For industrial enterprises, while the Industrial Enterprise Environmental Statistics Database contains detailed energy consumption data that can accurately calculate their carbon emission levels, it lacks energy consumption indicators after 2011, limiting its usable years to only up to 2011 (Song Deyong et al., 2024). It is worth noting that, with continuous updates and improvements, the National Tax Survey Database offers a new solution to this research dilemma. This database not only contains detailed energy consumption data for various enterprise segments, enabling accurate calculation of carbon emission levels, but the version currently available in this chapter has been updated to 2020, making it superior to the Industrial Enterprise Environmental Statistics Database in terms of timeliness. Therefore, this paper uses carbon emission data calculated from the National Tax Survey Database for research, providing a reliable data foundation for subsequent empirical analysis.

3.2. Model Construction

To test the impact of Intelligent Manufacturing on the carbon emission intensity of enterprises, this chapter constructs the following benchmark regression model:

$$CI_{it} = \beta_0 + \beta_1 IM_{it} + \beta_n controls_{it} + \varphi_i + \mu_t + \varepsilon_{it} \tag{1}$$

Here, i, t represent the enterprise and the year respectively, CI_{it} is the carbon emission intensity of the enterprise, IM_{it} is the intelligent manufacturing level of the enterprise, $controls_{it}$ is the control variable at the enterprise level, φ_i and μ_t represents the fixed effects of the enterprise and the year respectively, ε_{it} is the random disturbance term for clustering at the enterprise level. This chapter focuses on the β_1 coefficients. If Intelligent Manufacturing has effectively driven corporate carbon reduction, it should be significantly negative.

$$CO_{2,it} = \sum_{k=1}^{K} Energy_{k,it} \cdot EF_k \tag{2}$$

Where，$Energy_{k,it}$ is consumption of energy type k；EF_k is carbon emission factor for energy type k. Then define:

$$CI_{it} = \frac{CO_{2,it}}{Revenue_{it}} \tag{3}$$

Carbon emissions are calculated by multiplying enterprise-level energy consumption by the carbon emission factor for a specific energy source. The emission factor adopts the recommended values from the "Guidelines for the Compilation of Provincial Greenhouse Gas Inventories (Trial)" (e.g., raw coal: 2.776 tCO_2/tce, natural gas: 1.910 $tCO_2/10^4m^3$). Energy consumption is derived from the "Energy Purchase, Consumption and Inventory" table in the State Taxation Administration's Enterprise Survey Database, and the unit is uniformly converted to tons of standard coal (tce).

3.3 Variable Definitions

(1) Explained variable: Carbon emission intensity (CI) The energy consumption breakdown data contained in the China Tax Survey database provides a reliable data source for calculating carbon emissions at the enterprise level. This chapter calculates carbon emission levels based on the consumption data of coal and oil in enterprises (Li Zhiguo et al., 2024a; Tu Xiwei and Zhang Pingdan, 2024).

(2) Explanatory Variable: Intelligent Manufacturing (IM) This study uses listed company annual reports and patent texts as a corpus to construct a Intelligent Manufacturing dictionary based on the Word2Vec model (Mikolov et al., 2013) and to build an index of enterprise Intelligent Manufacturing level. The construction process consists of three steps: First, data collection and preprocessing. Important policy documents and research reports in the field of Intelligent Manufacturing are selected, and relevant Intelligent Manufacturing terms are extracted manually as seed words. Then, the listed company annual reports and patent texts are preprocessed. Second, referring to Li Maolin et al. (2024), Yao Jiaquan et al. (2024), and Li et al. (2021), the Word2Vec model (Mikolov et al., 2013) is used. Using the preprocessed listed company annual reports and patent texts as a corpus, machine learning methods are used to find synonyms of Intelligent Manufacturing seed words to expand the dictionary. The Skip-gram model is trained based on the gensim toolkit in Python. The model parameters were set as follows: five words were extracted to the left and five to the right of the central word; the dimension of the word vector was 300; the number of iterations was 5; the threshold for truncating the dictionary was 5; and the learning algorithm was Hierarchical Softmax (Yao Jiaquan et al., 2024). Finally, an enterprise intelligent manufacturing index was constructed. The logarithmic value of the frequency of intelligent manufacturing-related words in the enterprise's annual report text was incremented by 1 to measure the enterprise's intelligent manufacturing level. This index is the independent variable IM studied in this study.

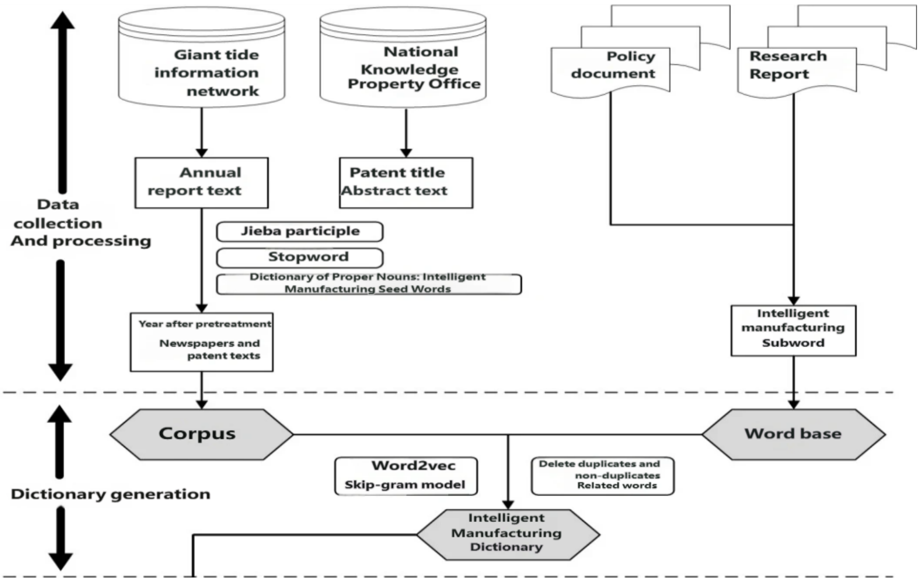

Figure 1： Explanatory Variable construction process

(3) Control variables

Table 1: Variable symbols and measurement methods

Variable Name	Variable Symbol	Variable Measurement Method
Carbon emission intensity	CI	As mentioned above
Intelligent manufacturing	IM	As mentioned above
Leverage Ratio	LEV	Total Liabilities / Total Assets
Company size	SIZE	Logarithm of Total Assets + 1
Number of staffs	STAFF	Logarithm of Average Annual Number of Employees + 1
Age of establishment	AGE	Logarithm of Years Since Establishment + 1
Percentage of fixed assets	FIX	Fixed Assets / Total Assets
Return on assets	ROA	Total Profit / Fixed Assets at Year-End
Industry Concentration	HHI	Industry Herfindahl Index
Equity Concentration	TOP5	Shareholding Ratio of the Top Five Shareholders

It is important to emphasize that the fixed-effects model in this paper primarily controls for the combined impact of inherent firm characteristics and time, but cannot completely exclude endogeneity caused by unobserved heterogeneity (such as entrepreneurs' environmental awareness and the level of greening in the supply chain). Therefore, the conclusion of this paper should be understood as 'a significant negative correlation exists between the level of intelligent manufacturing and carbon intensity', rather than a strict causal effect. Future research can further identify causal chains using quasi-experimental designs (such as the impact of the Ministry of Industry and Information Technology's 'intelligent manufacturing pilot demonstration' policy) and instrumental variable methods (such as using the industry average intelligent penetration rate as an IV).

4. Analysis of Empirical Results

4.1 Benchmark regression results

This study uses a regression model for empirical analysis to explore the causal relationship between intelligent manufacturing and corporate carbon emission intensity. Table 2 shows the baseline regression results. Column (1) only includes the key explanatory variable, intelligent manufacturing, for regression. The results show that the coefficient of IM is significantly negative at the 1% level. Columns (2) and (3) progressively include control variables, year, and corporate fixed effects. It can be seen that the coefficient of IM remains negative and significant at the 1% level, indicating that intelligent manufacturing effectively promotes the reduction of corporate carbon emission intensity, verifying the hypothesis proposed in this paper. From the perspective of control variables, the regression coefficient for firm size (SIZE) is significantly negative, indicating that the intensive operation of larger firms can effectively reduce their carbon emission intensity. The regression coefficient for number of employees (STAFF) is significantly positive, verifying that the collective action dilemma of multi-employee firms will hinder their carbon emission reduction. The regression coefficient for age (AGE) is positive and significant, indicating that the inertia of low-carbon transformation in firms with longer establishment times increases their carbon emission intensity. The regression coefficient for fixed asset ratio (FIX) is positive and significant, verifying that firms with larger fixed assets consume more energy in their production processes and require additional maintenance resources, thereby increasing their carbon emission intensity. The regression coefficient for return on assets (ROA) is negative and significant, verifying that firms with stronger profitability are more motivated to invest in energy-saving and emission-reduction projects, thereby reducing their carbon emission intensity.

Table 2: Benchmark Regression Results

	CI	CI	CI
	(1)	(2)	(3)
IM	-0.1230 * * *	-0.0652 * * *	-0.0431 * * *
	(0.0142)	(0.0109	(0.0131)
LEV		0.1880 * *	0.0644
		(0.0914	(0.1288)
SIZE		-0.1371 * * *	-0.3053 * * *
		(0.0220)	(0.0632)
STAFF		0.0759 * * *	0.1032 * *
		(0.0212)	(0.0437)
AGE		-0.0015	0.2544 * *
		(0.0343)	(0.1149)
FIX		1.1104 * * *	0.4894 * * *
		(0.1826)	(0.1693)
ROA		-0.4293 * * *	-0.2849 * *
		(0.1130)	(0.1275)
HHI		-0.0757	0.0196
		(0.0943)	(0.1043)
TOP5		0.0674	-0.1328
		(0.0781)	(0.1065)
CONS	0.3412 * * *	2.3113 * * *	5.3740 * * *
	(0.0315)	(0.3646)	(1.1933)
Year fixed	no	no	yes
Enterprise fixed	no	no	yes
Observations	8268	8268	8268
Adj-R2	0.0255	0.1408	0.5852

Note: *, **, and *** respectively indicate significance at the 10%, 5%, and 1% levels; The values in parentheses represent robust standard errors for clustering at the enterprise level

Corporate carbon intensity is the ratio of total corporate carbon emissions to operating revenue. So, what are the underlying causes of the reduction effect of intelligent Manufacturing on corporate carbon intensity? Is it due to a decrease in total carbon emissions, an increase in operating revenue, or a combination of both? This chapter conducts regression tests on this question, using the logarithm of total corporate carbon emissions plus 1 (CE) and the logarithm of operating revenue plus 1 (REV) as dependent variables, and Intelligent Manufacturing as the independent variable. The results are shown in table 3. The results indicate that Intelligent Manufacturing has a significantly negative impact on total corporate carbon emissions (CE) and a significant positive impact on corporate operating revenue (REV). Therefore, Intelligent Manufacturing both promotes a decrease in total corporate carbon emissions and increases corporate operating revenue, thus jointly reducing corporate carbon intensity. It is worth noting that the decline in carbon intensity (CI) may stem from a decrease in the numerator (CE) and an increase in the denominator (REV), or both. The mechanistic test in this paper (Table 3) shows that the coefficient of IM to CE is −0.082 ($p<0.01$), and the coefficient to REV is 0.137 ($p<0.01$), indicating that IM directly suppresses emissions and also expands revenue through improved efficiency and quality. Therefore, the decline in CI reflects genuine “dual carbon reduction”—that is, a substantial reduction in physical emissions per unit of output—rather than a statistical illusion of mere financial expansion.

Table 3: The impact of Intelligent Manufacturing on total carbon emissions and operating revenue

	CE	REV
	（1）	（2）
IM	-0.0783***	0.0087**
	（0.0245）	（0.0043）
Control variables	YES	YES
Year fixed	YES	YES
Company fixed	YES	YES
Number of observations	8268	8268
Adj-R2	0.5762	0.9732

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses are the robust standard errors of the firm-level clustering.

5. Conclusion

The benchmark regression results demonstrate that intelligent manufacturing effectively promotes a reduction in corporate carbon emission intensity. Currently, some enterprises are still facing a lack of motivation in promoting carbon emission reduction. On the one hand, traditional emission reduction methods, such as end-of-pipe treatment equipment and energy substitution, often require huge capital investments, and the high cost barrier deters many enterprises, especially small and medium-sized enterprises. On the other hand, some enterprises' emission reduction measures suffer from low technological content and poor adaptability to their own conditions, resulting in insignificant emission reduction effects per unit of investment and making it difficult to form a virtuous cycle. This dual constraint leads to persistently high corporate carbon emission intensity. Against this backdrop, the empirical research findings in this chapter provide a new approach to breaking this dilemma. This study found a robust and significant negative correlation between improved intelligent manufacturing levels and reduced corporate carbon emission intensity, providing micro-level evidence to support the "digital empowerment of green transformation."

Reference

Chen S., Zhang S., Zeng Q., Li Y., 2023, Can artificial intelligence achieve carbon neutrality? Evidence from a quasi-natural experiment, Frontiers in Ecology and Evolution, 11, Article 1151017.

Chen X., Despeisse M., Johansson B., 2020, Environmental sustainability of digitalization in manufacturing: A review, Sustainability, 12(24), 10298.

Fang H., Jiang C., Hussain T., 2022, Input digitization of the manufacturing industry and carbon emission intensity based on testing the world and developing countries, International Journal of Environmental Research and Public Health, 19(19), 12855.

Feng Z.Y., Song D.L., Xie W.S., 2023, How does the digital economy facilitate China’s dual-carbon goals? Basic pathways, internal mechanisms, and policy strategies, Beijing Normal University Journal (Social Sciences), 295(1), 52–61.

Huang Zhuo, Tao Yunqing, Liu Zhaoda, Ye Yongwei. Intelligent manufacturing, human capital upgrading and enterprise labor income share [J]. Journal of Economics (Quarterly),2024b,24(05):1412-1427.

Hu S.L., Zeng G., Wang S.P., 2025, Spatiotemporal evolution and technological innovation-driven decarbonization and pollution reduction in the Yangtze River Economic Belt, Geographical Research, 44(1), 72–90.
Hu Y.M., Guo C.X., 2023, Research on the impact of digitalization on carbon emission intensity of manufacturing enterprises: Theoretical modeling and mechanism testing, Journal of Beijing University of Technology (Social Sciences Edition), 23(5), 153–168.
Hui Lili, Xie Huobao. Intelligent manufacturing, innovation culture and enterprise cost stickiness [J]. Management Review, 24,36(05):178-193.
Jiang Wei, Gong Sihao, Li Xitao. Robot Shock, Capital-embodied technological progress and manufacturing carbon reduction: Theoretical Analysis and Empirical Evidence from China [J]. China Industrial Economics,2022,(10):24-42.
Jiang Wei, Ni Shicheng, Peng Miao. Efficiency Transformation of Digital Technology Enterprises Empowering Real Economy Development: Theoretical and Empirical Evidence from the Perspective of Digital Supply Chain [J]. Quantity Economics & Technology Economics, 2020,42(01):51-71.
Jin Xiangyi, Zhang Wenfei. Indirect digital transformation, supply chain spillover and corporate export trade [J]. The Journal of World Economy,2024,47(10):3-30.
Jose R., Panigrahi S.K., Patil R.A., 2020, Artificial intelligence-driven circular economy as a key enabler for sustainable energy management, Materials Circular Economy, 2, Article 1.
Kulkov I., 2021, The role of artificial intelligence in business transformation: A case of pharmaceutical companies, Technology in Society, 66, 101629.
Li Bin, Yang Ran, Lu Juan, Jia Zhen. Enterprise Digital Transformation, Supply Chain Spillover and Labor Skill Bias [J]. Quantitative & Technical Economics, 24,41(08):133-153.
Li Jianjun, Wu Zhouyi. The tax dividend of robot use: From the perspective of New Quality Productivity [J]. Management World, 24,40(06):1-15.
Li Lei, Wang Xiaoxia, Bao Qun. The employment effect of robots: Mechanisms and Chinese Experience [J]. Management World,2021,37(09):104-119.
Li Maolin, Wang Zilu, He Guanghui, Wang Yukun. Financial technology innovation in banking, structural inclusive effects and entrepreneurial vitality [J]. Management World,2024,40(06):195-224.
Li Wenjing, Zheng Manni. Substantive innovation or strategic innovation? -- The impact of macro industrial policies on Micro Enterprise innovation [J]. Economic Research Journal,2016,51(04):60-73.
Mao Q.L., Shi B.C., 2024, The road to green development: Intelligent manufacturing and enterprise green transformation, The World Economy, 47(9), 152–182.
Masood A., Ahmad K., 2021, A review on emerging artificial intelligence (AI) techniques for air pollution forecasting: Fundamentals, application and performance, Journal of Cleaner Production, 322, 129072.
Pournader M., Ghaderi H., Hassanzadegan A., 2021, Artificial intelligence applications in supply chain management, International Journal of Production Economics, 241, 108250.
Stavropoulos P., Panagiotopoulou V.C., Papacharalampopoulos A., 2022, A framework for CO_2 emission reduction in manufacturing industries: A steel industry case, Designs, 6(2), 22.
Tang L., Lu B., Tian T., 2023, The effect of input digitalization on carbon emission intensity: An empirical analysis based on China's manufacturing, International Journal of Environmental Research and Public Health, 20(4), 3174.
Xiang T.D., 2017, Research on regional carbon emission efficiency and total factor productivity in China: Based on three-stage DEA model, Economic Survey, 34(1), 20–25.
Yang G., Wang F., Deng F., 2023, Impact of digital transformation on enterprise carbon intensity: The moderating role of digital information resources, International Journal of Environmental Research and Public Health, 20(3), 2178.
Yang Z., Gao W., Han Q., 2022, Digitalization and carbon emissions: How does digital city construction affect China's carbon emission reduction?, Sustainable Cities and Society, 87, 104201.
Yi Y., Cheng R., Wang H., 2023, Industrial digitization and synergy between pollution and carbon emissions control: New empirical evidence from China, Environmental Science and Pollution Research, 30(13), 36127–36142.
Zeng C.H., Wang N.J., 2022, Research on influencing factors of ecological competitiveness of small and micro enterprises from the perspective of digital empowerment, Ecological Economy, 38(1), 77–83.