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Intelligent Manufacturing, Enterprise ESG Performance and Green Total Factor Productivity: A Case Study of Strategic Emerging Industries

Yan Li[1,2], Mu Zhang[1,2*], Wangjing Xu[1,2]

[1]School of Applied Economics, Guizhou University of Finance and Economics, Guiyang, China
[2]Guizhou Institution for Technology Innovation & Entrepreneurship Investment, Guizhou University of Finance and Economics, Guiyang, China
Email: *zhangmu01@163.com

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Abstract

As a brand-new production technology, the development and application of intelligent manufacturing can improve corporate development strategies and help firms gain competitive advantages. However, whether its development can further enhance corporate green total factor productivity and through what mechanisms it works are new issues that remain to be clarified. Using data from 523 listed companies in China's strategic emerging industries from 2013 to 2024, this paper empirically examines the impact of intelligent manufacturing development on corporate green total factor productivity and its underlying mechanisms, and further explores the heterogeneity of this impact. The findings are as follows: First, intelligent manufacturing development positively promotes the improvement of corporate green total factor productivity, and this conclusion remains valid after a series of endogeneity treatments and robustness checks. Second, the level of green technology innovation and corporate ESG performance play a chain mediating role between intelligent manufacturing development and corporate green total factor productivity. Third, the impact of intelligent manufacturing development on corporate green total factor productivity exhibits significant differentiated characteristics with respect to firm ownership type and sub-industry nature; specifically, non-state-owned firms and firms in the new-generation information technology industry and high-end equipment manufacturing industry are more sensitive to intelligent manufacturing development in terms of green total factor productivity. The conclusions of this paper deepen the understanding of the causal relationship between intelligent manufacturing development and corporate green total factor productivity, and provide theoretical guidance for firms to actively develop intelligent manufacturing and enhance green total factor productivity.

Keywords

Intelligent Manufacturing, Green Technology Innovation, Corporate ESG Performance, Green Total Factor Productivity, Strategic Emerging Industries

1. Introduction

Green total factor productivity (GTFP) is a comprehensive indicator of both economic and environmental benefits and also serves as a yardstick for measuring the effectiveness of green economic development. It plays a significant role in enhancing resource efficiency, strengthening competitiveness, and promoting sustainable development (Lin & Tan, 2019). GTFP is not only an endogenous driver of economic growth but also a rigid constraint on the scale and speed of development (Li & Tao, 2012). Compared with traditional total factor productivity, GTFP more accurately assesses the production performance of regions or firms, provides a scientific basis for policy-making, and more precisely reflects economic realities (Shen & Tang, 2024).

The systematic formation of intelligent manufacturing thinking stems from the rapid development of computer and information technologies, involving a range of key technologies. It is an inevitable outcome of the comprehensive evolution and integration of modern manufacturing technology, computer science and technology, artificial intelligence, and related fields (Tao, Liu, & Kusiak, 2018). As a deep integration of the new generation of information technology and manufacturing technology, intelligent manufacturing can significantly improve corporate operational efficiency, enhance profitability, and promote sustainable corporate development (Li, 2022). Through a series of advanced technical means, intelligent manufacturing precisely controls material and energy consumption in production processes, reduces waste, and markedly improves overall production efficiency. At the same time, it also enables green development for enterprises and serves as a key approach for firms to achieve green, low-carbon, and efficient production (Tan et al., 2019; Lyu & Han, 2015; Wang & Li, 2018; Chen, 2022b; Wang & Han, 2020).

Most existing studies focus on the impact of intelligent manufacturing on corporate production costs (Abdallah, Shehab, & Al-Ashaab, 2021), productivity (Zhou et al., 2019), financial performance (Chen & Li, 2022), and innovation Esposito (Esposito De Falco et al., 2017), among other aspects. Few studies in the extant literature have examined the effect of intelligent manufacturing on corporate GTFP, and even fewer have incorporated both the level of green technology innovation and corporate ESG performance into the same analytical framework.

As social attention to corporate GTFP gradually increases, some scholars have begun to concentrate on this area. Research finds that intelligent manufacturing development promotes corporate GTFP (Yan & Zhao, 2024; Chen, He, & Liu, 2024), and the underlying mechanisms include enhancing corporate green technology innovation capability (Yan & Zhao, 2024), optimizing human capital structure (Yan & Zhao, 2024), promoting green technological progress (Chen, He, & Liu, 2024), and improving green technical efficiency (Chen, He, & Liu, 2024).

Green technology innovation emphasizes driving green improvements and upgrades in products, services, processes, and other aspects through scientific and technological innovation and management innovation (Ahmed et al., 2022). Studies show that enhancing corporate green technology innovation capability contributes to improving the level of corporate sustainable operations (Wang & Xie, 2022). By reducing pollutant emissions and resource consumption through green technology innovation, firms can lower environmental risks and compliance costs (Lu, Zhou, & Dou, 2023), which reflects their emphasis on environmental protection. Such emphasis facilitates the strengthening of corporate ESG disclosure. Good ESG performance, in turn, can optimize resource allocation, enhance social responsibility image, broaden financing channels, improve corporate governance structures, increase decision-making transparency, alleviate financing constraints, and optimize human capital structure (Zhou, Pan, & Fu, 2020), thereby helping to boost GTFP (Ding & Bai, 2024). Therefore, exploring the mediating roles of green technology innovation capability and corporate ESG performance in the relationship between intelligent manufacturing development and corporate GTFP is of great value for deepening the understanding of the causal link between the two.

The possible marginal contributions of this paper are as follows. First, by introducing corporate ESG performance into the existing pathway of "intelligent manufacturing development → green technology innovation → green total factor productivity," this paper thoroughly examines the mechanism through which firms enhance their GTFP by improving intelligent manufacturing development, which in turn raises the level of green technology innovation and subsequently improves ESG performance. That is, we investigate the pathway of "intelligent manufacturing development → green technology innovation → corporate ESG performance → green total factor productivity," thereby extending and deepening the understanding of the mechanisms through which intelligent manufacturing development affects corporate GTFP. Second, this paper examines the heterogeneity in terms of ownership type and sub-industry of the impact of intelligent manufacturing development on GTFP of firms in strategic emerging industries, thus enriching the heterogeneity analysis of this impact.

The remainder of this paper is structured as follows. Section 2 presents the theoretical analysis and research hypotheses. Section 3 describes the empirical design. Section 4 reports the empirical results and analysis. Section 5 provides the discussion and conclusions.

2. Theoretical Analysis and Research Hypotheses

2.1. The Impact of Intelligent Manufacturing Development on Green Total Factor Productivity of Firms in Strategic Emerging Industries

The development of intelligent manufacturing makes firms' production methods more flexible and versatile, optimizing data-driven processes, human-machine collaboration, and supply chains, thereby greatly enhancing the development potential and adaptability of existing firms (Zhao, 2023). The growth paths of green total factor productivity (GTFP) mainly consist of economic growth and environmental pollution reduction (Sun & Saat, 2023). In terms of economic growth, intelligent manufacturing, by leveraging advanced information technology, automation technology, and artificial intelligence, enables intelligent management and control of production processes, improves production efficiency, and injects new vitality into economic growth (Huang et al., 2023). Intelligent manufacturing also enhances firm competitiveness, which helps firms expand market share and improve profitability, thus contributing to economic growth (Qiao & Zhao, 2025). In terms of environmental pollution reduction, through intelligent manufacturing technologies, firms can achieve effective management and utilization of waste, thereby reducing resource consumption and environmental pollution and promoting resource recycling (Zhang et al., 2023). In addition, by introducing new technologies, new materials, and new processes, intelligent manufacturing continuously optimises product design and production processes, increasing product added value and competitiveness. These new technologies and processes often feature lower energy consumption and higher environmental performance, helping firms achieve green development (Zhang, 2023). In summary, this paper proposes research hypothesis H1:

H1: Intelligent manufacturing development has a significant positive impact on the green total factor productivity of firms in strategic emerging industries.

2.2. The Mechanism through Which Intelligent Manufacturing Development Affects Green Total Factor Productivity of Firms in Strategic Emerging Industries

Currently, the rise of intelligent manufacturing on a global scale is leading a new wave of innovation centred on "green development" (Zhu, Liang, & Wu, 2020). By highly integrating informatisation, automation, and intelligent technologies, intelligent manufacturing accurately identifies the environmental pollution challenges and green product demands faced by firms, thereby greatly improving problem-solving efficiency, resource utilization, and product quality. This development model not only promotes industrial transformation and upgrading but also provides broad space and strong support for green technology innovation (Li et al., 2022). Although corporate green technology innovation activities are accompanied by many challenges, including high risks and uncertainty, long-term financial and time investments, and complex and cumbersome implementation processes, in the long run, green technology innovation driven by intelligent manufacturing can substantially reduce environmental pollution and resource consumption in production processes, lower environmental risks, and enhance corporate reputation, all of which help firms achieve better ESG performance (Xu, Qiao, & Huang, 2023).

On the one hand, good corporate ESG performance highlights firms' efforts and achievements in energy conservation, environmental protection, and sustainable development, while also providing abundant information for stakeholders such as investors. Such information transparency reduces the costs and difficulties for stakeholders to obtain firm-related information, enabling them to monitor firm operations more conveniently (Li & Li, 2023). Under such monitoring pressure, firms are motivated to optimize internal production processes and improve management efficiency (Zhang, Wang, & Song, 2024), thereby reducing management costs. These measures collectively help firms build competitive advantages in productivity (Du & Jin, 2021). On the other hand, good ESG performance helps firms optimise governance structures, improve information transparency, effectively alleviate principal-agent conflicts and information asymmetry, and consequently help firms curb inefficient investment behaviours, ultimately enhancing capital allocation efficiency (Dai, Zhang, & Pan, 2019). Sound decision-making and transparent information disclosure help firms identify and resolve potential problems in a timely manner, optimise resource allocation, and improve production efficiency (Chen, 2022a). In summary, this paper proposes research hypothesis H2:

H2: The level of green technology innovation and corporate ESG performance play a chain mediating role between intelligent manufacturing development and green total factor productivity of firms in strategic emerging industries.

2.3. Heterogeneity of the Impact of Intelligent Manufacturing Development on Green Total Factor Productivity of Firms in Strategic Emerging Industries

Previous studies have shown that the impact of intelligent manufacturing development on corporate green total factor productivity exhibits scale heterogeneity (Yan & Zhao, 2024), regional heterogeneity (Yan & Zhao, 2024), industry heterogeneity (Chen, He, & Liu, 2024), and other forms of heterogeneity. This paper further analyses the heterogeneity with respect to ownership type and sub-industry in the impact of intelligent manufacturing development on GTFP of firms in strategic emerging industries.

1) *Nature of Ownership*

State-owned enterprises (SOEs) are generally supported and protected by national policies, giving them strong resilience against economic fluctuations and market changes. While fulfilling their social responsibilities of promoting scientific and technological innovation and economic development, SOEs also make significant contributions to society (Garde-Sánchez, López-Pérez, & López-Hernández, 2018). The business objectives of SOEs often exhibit diversified characteristics, whereas their management mechanisms tend to be relatively traditional and rigid, which may, to some extent, constrain their vitality in technological innovation. Consequently, SOEs start from a smaller base in terms of GTFP, and the application of intelligent manufacturing technologies can more effectively leverage their advantages and improve GTFP to a greater extent (Yan & Zhao, 2024). In addition, SOEs often attract higher levels of national attention, and the government encourages them to adopt advanced environmental protection technologies and production processes through policy guidance and incentive mechanisms, thereby promoting green development and sustainable operations (Chen, 2023). These policies and measures provide strong guarantees for improving the GTFP of SOEs (Yan & Zhao, 2024). By contrast, non-state-owned enterprises operate with more flexible mechanisms and higher decision-making efficiency, and may thus be able to apply intelligent manufacturing technologies to production practices and translate them into green production performance more quickly. Therefore, this paper proposes research hypothesis H3a:

H3a: The impact of intelligent manufacturing development on the green total factor productivity of firms in strategic emerging industries exhibits heterogeneity with respect to ownership type.

2) *Nature of Sub-industries within Strategic Emerging Industries*

Strategic emerging industries are industries based on major technological breakthroughs and major development needs, which play a significant leading and driving role in the overall and long-term development of the economy and society. These industries are knowledge- and technology-intensive, consume few material resources, have great growth potential, and yield high comprehensive benefits. They include nine major areas: the new-generation information technology industry, the high-end equipment manufacturing industry, the new materials industry, the biotechnology industry, the new energy vehicle industry, the new energy industry, the energy-conservation and environmental protection industry, the digital creative industry, and related service industries (as classified in the Strategic Emerging Industries Classification (2018), National Bureau of Statistics Order No. 23). Since each sub-industry differs considerably in terms of industry attributes, technological intensity, foundation for intelligent transformation, and demand for green production, among many other aspects, the impact of intelligent manufacturing development on GTFP of firms in each sub-industry also varies substantially. Accordingly, this paper proposes research hypothesis H3b:

H3b: The impact of intelligent manufacturing development on the green total factor productivity of firms in strategic emerging industries exhibits heterogeneity with respect to sub-industry.

3. Empirical Design

3.1. Sample Selection and Data Sources

This paper takes the sample firms of China's Strategic Emerging Industries Comprehensive Index (000891) as the research sample, with the sample period ranging from 2013 to 2024. The specific data sources are as follows: data for measuring green total factor productivity are obtained from the China City Statistical Yearbook, the China Environmental Statistical Yearbook, corporate social responsibility reports, and annual reports of listed companies; data for measuring the level of intelligent manufacturing development are derived from annual reports of listed companies; data on green technology innovation are sourced from the website of the National Intellectual Property Administration; data for measuring corporate ESG performance are obtained from Shanghai Huazheng Index Information Service Co., Ltd.; and control variable data are sourced from the CSMAR database and the Wind database. The sample screening and processing procedures are as follows: 1) exclude sample firms with abnormal trading status such as ST, *ST, and PT; 2) exclude samples with abnormal data; 3) exclude samples with missing key data values; 4) exclude sample firms that have been listed for less than one year; and 5) winsorise continuous variables at the 1st and 99th percentiles. Ultimately, we obtain 523 sample firms across eight sub-industries within strategic emerging industries (note: the sample size for the related service industry is zero), yielding a total of 5432 observations, thus forming an unbalanced panel dataset.

3.2. Variable Definitions

3.2.1. Dependent Variable: Green Total Factor Productivity (GTFP)

Following the approach of Yan & Zhao (2024), this paper employs the non-radial SBM-GML index to measure corporate green total factor productivity (GTFP). The specific measures of input and output indicators for GTFP are as follows: 1) Factor inputs: labour input is proxied by the number of employees; capital input is proxied by net fixed assets; energy input is proxied by the industrial electricity consumption of the city where the firm is located, converted according to the proportion of the firm's employees to the city's total urban employment. 2) Desirable output: the firm's operating revenue is used as the proxy variable for desirable output. 3) Undesirable output: following Cui & Lin (2019), we convert the emissions of "industrial three wastes" (industrial SO_2, industrial wastewater, and industrial smoke and dust) based on the proportion of the firm's employees to the city's total urban employment, and use these as proxy variables for undesirable output.

3.2.2. Independent Variable: Intelligent Manufacturing Development Level (IM)

Regarding the measurement of corporate intelligent manufacturing development level, this paper follows the method of Yu et al. (2020) to construct an indicator of intelligent manufacturing development. The specific steps are as follows: 1) collect and summarise the annual reports of sample firms; 2) extract 57 keywords related to corporate intelligent manufacturing development (Made in China 2025, Industry 4.0, Internet+, automation, informatisation, information management, information application, digitalisation, networking, integration, virtualisation, intelligence, Internet of Things, virtual reality, 3D printing, artificial intelligence, biometrics, pattern recognition, neural networks, cloud computing, cloud platform, cloud services, cloud technology, big data, massive data, data centre, data storage, data analysis, data mining, Internet, mobile Internet, interconnection, robotics, industrial robots, CNC machine tools, CNC systems, sensors, intelligent logistics, intelligent services, intelligent terminals, green manufacturing, high-end equipment manufacturing, military-civilian integration, smart grid, energy Internet, smart energy, smart home, smart city, smart transportation, smart healthcare, smart community, e-government, new energy vehicles, electric vehicles, electric cars, power battery, and charging piles); 3) use Python software to conduct text analysis and word frequency statistics on the annual reports of sample firms; 4) aggregate the word frequency counts for intelligent manufacturing development of each sample firm in the given year.

3.2.3. Mediating Variables

1) Green technology innovation level (GI). Following Gui (2025), this paper uses the number of granted green patents to measure corporate green technology innovation.

2) Corporate ESG performance (ESG). Following Ding & Bai (2024), this paper uses the Huazheng ESG rating to measure corporate ESG performance. Huazheng Index classifies ESG ratings into nine grades from C to AAA, with corresponding scores from 1 to 9. Ratings are assigned quarterly, and we take the average of the four quarterly scores to represent corporate ESG performance; higher scores indicate better ESG performance.

3.2.4. Control Variables

To ensure the robustness of the results, drawing on existing studies (Yan & Zhao, 2024; Chen, He, & Liu, 2024), this paper selects five control variables: return on total assets (ROA), cash flow (Cashflow), inventory-to-total-assets ratio (Inv), operating revenue growth rate (Growth), and board size (Board). The definitions and descriptions of the main variables are presented in **Table 1**.

Table 1. Definitions and descriptions of main variables.

Type	Variable Name	Symbol	Definition and Description
Dependent Variable	Green Total Factor Productivity	GTFP	Measured by the SBM-GML index
Independent Variable	Intelligent Manufacturing Development Level	IM	Natural logarithm of total word frequency of intelligent manufacturing plus one
Mediating Variables	Green Technology Innovation Level	GI	Natural logarithm of the number of granted green patents plus one
	Corporate ESG Performance	ESG	Huazheng ESG rating
Control Variables	Return on Total Assets	ROA	Ratio of net profit to total assets at period-end

Continued

Cash Flow	Cashflow	Ratio of net cash flow from operating activities to total assets
Inventory-to-Total-Assets Ratio	Inv	(Inventory balance ÷ Total assets) × 100%
Operating Revenue Growth Rate	Growth	(Current operating revenue − Previous operating revenue)/Previous operating revenue
Board Size	Board	Natural logarithm of the total number of board members

3.3. Model Specification

To examine the impact of intelligent manufacturing development level on corporate green total factor productivity and its mechanisms, we specify the following two-way fixed effects model:

$$\mathrm{GTFP}_{it} = \alpha_0 + \alpha_1 \mathrm{IM}_{it} + \alpha_2 \mathrm{Controls}_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (1)$$

where GTFP denotes corporate green total factor productivity, IM denotes corporate intelligent manufacturing development level, and Controls denote the control variables. In addition, λ_i and μ_t represent individual fixed effects and year fixed effects, respectively, and denotes the random error term.

Most existing studies employ the stepwise method proposed by Baron and Kenny (1986) for mediation effect testing. However, Jiang (2022) points out that the main problem in current mediation analysis is the misuse of the stepwise method borrowed from psychology, which leads to biased mediation effect tests. In light of this, we follow the operational recommendations for mediation analysis proposed by Jiang (2022) and construct the mediation effect test models as shown in Equations (2) and (3):

$$\mathrm{GI}_{it} = \beta_0 + \beta_1 \mathrm{IM}_{it} + \beta_2 \mathrm{Controls}_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (2)$$

$$\mathrm{ESG}_{it} = \gamma_0 + \gamma_1 \mathrm{GI}_{it} + \gamma_2 \mathrm{Controls}_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (3)$$

where GI denotes the level of corporate green technology innovation, and ESG denotes corporate ESG performance.

All regressions in this paper control for firm fixed effects and year fixed effects, and we use firm-level clustered standard errors in the regression models. All regressions are conducted using Stata 17.0 software.

4. Empirical Results and Analysis

4.1. Descriptive Statistics

The descriptive statistics for all variables are presented in **Table 2**. The mean of GTFP is 1.475 with a standard deviation of 1.362, indicating that the GTFP level among sample firms remains unbalanced. The mean of IM is 1.916 with a standard deviation of 1.105, suggesting considerable variation in the level of intelligent manufacturing development across sample firms during the observation period.

In addition, both GI and ESG have relatively large standard deviations, indicating substantial differences among sample firms. The distributions of the remaining control variables are consistent with existing research findings.

Table 2. Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
GTFP	5432	1.475	1.362	0.116	8.124
IM	5432	1.916	1.105	0.000	4.564
GI	5432	1.399	1.287	0.000	4.898
ESG	5432	4.226	0.929	1.750	6.750
ROA	5432	0.032	0.057	−0.221	0.180
Cashflow	5432	0.045	0.055	−0.103	0.200
Inv	5432	0.129	0.076	0.005	0.397
Growth	5432	0.146	0.329	−0.450	1.964
Board	5432	2.128	0.182	1.609	2.565

4.2. Benchmark Regression Results

Table 3 reports the benchmark regression results for the impact of intelligent manufacturing development level on corporate green total factor productivity. Column (1) presents the regression results of Model (1) without any control variables; the coefficient of intelligent manufacturing development level (IM) is 0.050 with a t-value of 2.07, significant at the 5% level. Column (2) shows the regression results of Model (1) with all control variables; the coefficient of IM is 0.045 with a t-value of 1.88, significant at the 10% level. The benchmark regression results support Hypothesis H1, indicating that intelligent manufacturing development has a significant positive impact on the green total factor productivity of firms in strategic emerging industries.

Table 3. Benchmark regression results.

	(1)	(2)
Variables	GTFP	GTFP
IM	0.050**	0.045*
	(2.07)	(1.88)
ROA		1.360***
		(3.54)
Cashflow		0.118
		(0.35)
Inv		0.407
		(0.84)

Continued

Growth		0.397***
		(6.77)
Board		0.357**
		(2.13)
Constant	1.380***	0.471
	(29.90)	(1.26)
Observations	5432	5432
Adjusted R^2	0.532	0.546
Firm fixed	Yes	Yes
Year fixed	Yes	Yes

Note: t-statistics adjusted for firm-level clustering are reported in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively (same below).

4.3. Endogeneity Issues and Robustness Checks

4.3.1. Endogeneity Issues

To avoid potential estimation bias arising from endogeneity, we adopt the instrumental variable method for further examination. Following Chen et al. (2024), we use the one-period lagged intelligent manufacturing development level (L_IM) as the instrumental variable. Table 4 presents the results of the instrumental variable estimation. The instrumental variable passes both the under-identification test and the weak-instrument test, and the regression results are consistent with our earlier conclusions.

Table 4. Instrumental variable estimation results.

	(1)	(2)
	First Stage	Second Stage
Variables	IM	GTFP
L_IM	0.396***	
	(23.43)	
IM′ (Fitted value of IM from the first stage)		0.124***
		(2.59)
Controls	Yes	Yes
Constant	0.982***	
	(0.231)	
Observations	4735	4735
Adjusted R^2	0.729	0.028
Firm fixed	Yes	Yes

Continued

Year fixed	Yes	Yes
Kleibergen-Paap rk LM	0.000***	
Kleibergen-Paap Wald rk F	548.79	

Note: Column (1) reports the first-stage regression results, showing that the coefficient of the instrumental variable on the explanatory variable is significant at the 1% level. The Kleibergen-Paap rk LM statistic (under-identification test) is 170.59 with a p-value of 0.000, rejecting the null hypothesis of under-identification. The Kleibergen-Paap Wald rk F statistic (weak-instrument test) is 548.79, which exceeds the Stock-Yogo 10% critical value of 16.38, rejecting the null hypothesis of weak instruments. Overall, the instrumental variable is valid.

4.3.2. Robustness Checks

1) Replacement of the explanatory variable

Following Wen et al. (2022), and considering the substantial variation in the length of the MD&A section across annual reports of different listed firms, we measure the level of intelligent manufacturing through the following three steps: a) calculate the ratio of the frequency of keyword combinations for each sample firm to the total number of words in the firm's annual report; b) calculate the ratio of the firm's proportion to the total proportion of all sample firms in the same industry and same year; c) multiply this ratio by 100 to obtain the firm's intelligent manufacturing level. If no keywords appear in the annual report, the firm is assigned a value of 0 for that year.

2) 5% winsorization

Following Deng & Wu (2026), to eliminate potential estimation bias caused by extreme values, we winsorize all continuous variables at the 5th and 95th percentiles and re-estimate the coefficients in Model (1).

3) Exclusion of 2020 sample observations

Following Yan & Zhao (2024), and considering that the public health emergency in 2020 may have caused abnormal shocks to firms' production and operation activities that could bias the estimation results, we exclude the 2020 observations and re-run the benchmark regression.

Column (1) of **Table 5** reports the regression results after replacing the explanatory variable; the estimated coefficient of IM″ is 0.278, significant at the 5% level, indicating that the positive effect of intelligent manufacturing development on corporate GTFP remains robust even under alternative measurement approaches. Column (2) shows that the estimated coefficient of IM is 0.032, significant at the 10% level, suggesting that extreme values do not materially affect our core conclusion. Column (3) shows that the estimated coefficient of IM is 0.035, significant at the 10% level, consistent with the benchmark regression.

Taken together, these three robustness checks confirm that the benchmark results are robust and reliable, and that the positive effect of intelligent manufacturing development on GTFP of firms in strategic emerging industries is not driven by measurement choices, extreme values, or any specific year's observations.

Table 5. Robustness check results.

	(1)	(2)	(3)
	Replacement of the explanatory variable	5% winsorization	Exclusion of 2020 sample observations
Variables	**GTFP**	**GTFP**	**GTFP**
IM″	0.278**		
	(2.42)		
IM		0.032*	0.035*
		(1.72)	(1.79)
Controls	Yes	Yes	Yes
Constant	0.513	0.408	0.468
	(1.38)	(1.34)	(1.51)
Observations	5432	5432	4977
Adjusted R^2	0.547	0.553	0.548
Firm fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes

4.4. Mechanism Testing

By improving the level of intelligent manufacturing development, firms can promote the optimization and upgrading of industrial structures, shifting from traditional energy-intensive and high-emission production models to green, low-carbon, and environmentally friendly models, thereby providing broader space for green technology innovation. These innovative technologies help firms achieve resource conservation and reuse, reduce energy consumption and emissions, and improve ESG performance. Consequently, firms can realize optimal resource allocation and efficient utilization, thereby enhancing GTFP. Based on equations (2) and (3), we test the chain mediating role of green technology innovation level and corporate ESG performance in the relationship between intelligent manufacturing development and GTFP. Existing literature has already confirmed the impact of ESG performance on GTFP (Ding & Bai, 2024); therefore, we only examine the effects of intelligent manufacturing development on green technology innovation and of green technology innovation on ESG performance. The mechanism test results are shown in Table 6.

From Column (1) of Table 6, the estimated coefficient of IM is 0.087, significant at the 1% level; moreover, the 95% confidence interval [0.049, 0.125] does not contain zero, indicating significance at the 0.05 level. These results demonstrate that intelligent manufacturing development significantly promotes corporate green technology innovation. Column (2) shows that the estimated coefficient of GI is 0.107, significant at the 1% level, with a 95% confidence interval [0.063, 0.150] not containing zero, indicating significance at the 0.05 level. This suggests that improving green technology innovation significantly enhances ESG performance. Green technology innovation level and corporate ESG performance thus play a partial chain mediating role between intelligent manufacturing development and GTFP. In summary, intelligent manufacturing development exerts its positive effect through the chain pathway of "intelligent manufacturing → green technology innovation → corporate ESG performance → green total factor productivity," supporting Hypothesis H2.

Table 6. Mechanism test results.

	(1)	(2)
Variables	**GI**	**ESG**
IM	0.087***	
	(4.52)	
	[0.049, 0.125]	
GI		0.107***
		(4.76)
		[0.063, 0.150]
Controls	Yes	Yes
Constant	0.962***	3.705***
	(2.90)	(10.29)
Observations	5432	5432
Adjusted R^2	0.754	0.459
Firm fixed	Yes	Yes
Year fixed	Yes	Yes

4.5. Heterogeneity Analysis

In the heterogeneity analysis, we first divide the sample firms into two categories—state-owned enterprises and non-state-owned enterprises—based on ownership type (firms that changed ownership during the sample period are excluded), and conduct grouped regressions; the results are reported in Table 7. Second, following the Strategic Emerging Industries Classification (2018) (National Bureau of Statistics Order No. 23), we classify the sample firms into eight sub-industries—new-generation information technology, high-end equipment manufacturing, new materials, biotechnology, new energy vehicles, new energy, energy conservation and environmental protection, and digital creative industries—and run separate regressions (note: the related service industry has zero observations); the results are shown in Table 8.

Table 7 presents the grouped regression results for SOEs and non-SOEs. The estimated coefficient of IM for non-SOEs is 0.051, significant at the 5% level, while the coefficient for SOEs is 0.011 and not statistically significant. This indicates that the promoting effect of intelligent manufacturing development on GTFP is more pronounced in non-SOEs. A possible explanation is that non-SOEs have more flexible operating mechanisms and higher decision-making efficiency, enabling them to apply intelligent manufacturing technologies to production practices and translate them into green production performance more quickly. In contrast, although SOEs possess richer resources, their more complex organizational structures and diversified business objectives tend to delay the implementation and performance conversion of intelligent manufacturing technologies. Hypothesis H3a is thus supported.

Table 7. Heterogeneity analysis results (ownership type).

	(1)	(2)
	State-owned enterprises	Non-state-owned enterprises
Variables	**GTFP**	**GTFP**
IM	0.011	0.051**
	(0.32)	(3.30)
Controls	Yes	Yes
Constant	0.536	0.357
	(1.23)	(1.29)
Observations	1932	3490
Adjusted R^2	0.613	0.540
Firm fixed	Yes	Yes
Year fixed	Yes	Yes

Table 8. Heterogeneity analysis results (sub-industries).

	(1)	(2)	(3)	(4)
	NGITI	**HEMI**	**NMI**	**BI**
Variables	**GTFP**	**GTFP**	**GTFP**	**GTFP**
IM	0.055*	0.065**	−0.025	−0.010
	(1.84)	(2.09)	(−0.65)	(−0.24)
Controls	Yes	Yes	Yes	Yes
Constant	0.069	0.556	0.875	0.871
	(0.15)	(1.09)	(1.47)	(1.53)
Observations	1458	1067	876	849
Adjusted R^2	0.565	0.531	0.565	0.537
Firm fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
	(5)	**(6)**	**(7)**	**(8)**
	NEVI	**NEI**	**ESEPI**	**DCI**
Variables	**GTFP**	**GTFP**	**GTFP**	**GTFP**

Continued

IM	−0.041	−0.012	0.081	−0.868
	(−0.40)	(−0.33)	(1.47)	(−0.43)
Controls	Yes	Yes	Yes	Yes
Constant	1.121	1.236*	−2.132**	9.848
	(0.39)	(1.94)	(−2.10)	(0.33)
Observations	48	758	352	24
Adjusted R^2	0.582	0.560	0.564	0.242
Firm fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes

Note: NGITI = New-Generation Information Technology Industry; HEMI = High-End Equipment Manufacturing Industry; NMI = New Materials Industry; BI = Biotechnology Industry; NEVI = New Energy Vehicle Industry; NEI = New Energy Industry; ESEPI = Energy Conservation and Environmental Protection Industry; DCI = Digital Creative Industry.

Table 8 reports the grouped regression results for the eight strategic emerging sub-industries. The estimated coefficient of IM for the new-generation information technology industry is 0.055, significant at the 10% level; for the high-end equipment manufacturing industry, it is 0.065, significant at the 5% level; the coefficients for the other six sub-industries are not statistically significant. A plausible reason is that when sub-industries share common characteristics—high technological intensity, a strong foundation for intelligent transformation, and strong demand for green production—intelligent manufacturing technologies can be integrated into production processes more quickly, thereby enhancing GTFP more effectively. Hypothesis H3b is therefore supported.

5. Discussion and Conclusions

Taking 523 listed companies in China's A-share strategic emerging industries as the research sample, this paper employs a two-way fixed effects model to empirically examine the impact of intelligent manufacturing development on corporate green total factor productivity (GTFP) and its underlying mechanisms, and further conducts heterogeneity analyses by subdividing the sample according to ownership type and sub-industry. The main findings are as follows.

First, the level of intelligent manufacturing development significantly promotes the improvement of corporate GTFP. This conclusion remains robust after a series of endogeneity treatments and robustness checks.

Second, green technology innovation level and corporate ESG performance play a chain mediating role in the process through which intelligent manufacturing development affects corporate GTFP. Specifically, by implementing intelligent manufacturing and introducing new-generation information technologies such as big data, cloud computing, and artificial intelligence, firms gain strong technical support for green technology innovation, which drives the R&D and application of green technologies. This, in turn, optimizes production processes, reduces energy consumption and emissions during production, and improves production efficiency and quality. These improvements help firms lower costs, enhance profitability, and comprehensively improve ESG performance. Good ESG performance, in turn, improves resource utilization efficiency, strengthens environmental compliance, fulfils social responsibilities, improves stakeholder relations, enhances decision-making transparency and rationality, optimises resource allocation efficiency, and alleviates financing constraints. Together, these factors act on the production process and drive the steady improvement of GTFP.

Third, this promoting effect is more pronounced in non-state-owned enterprises and in firms within the new-generation information technology industry and the high-end equipment manufacturing industry. In terms of ownership type, the positive effect of intelligent manufacturing on GTFP is significant in non-SOEs but not in SOEs. This may be because non-SOEs have more flexible operating mechanisms and higher decision-making efficiency, enabling them to convert intelligent manufacturing technologies into green production performance more quickly. In terms of sub-industry, the impact of intelligent manufacturing is mainly concentrated in the new-generation information technology industry and the high-end equipment manufacturing industry, which are characterised by high technological intensity and a strong foundation for intelligent transformation, allowing intelligent manufacturing technologies to integrate more rapidly with production processes and generate green benefits.

Based on the above findings, this paper proposes the following policy recommendations.

First, firms should make intelligent manufacturing a long-term corporate development strategy, seize the opportunity of information technology transformation, actively implement intelligent manufacturing strategies, and strive to fully integrate intelligent manufacturing technologies into all aspects of production and operations. Firms should actively respond to China's advocacy for sustainable and high-quality development, improve production efficiency, and facilitate industrial transformation and upgrading. They should strengthen green technology innovation capabilities, improve ESG performance, increase R&D investment in green technologies, and embed the concept of green and sustainable development into corporate culture, thereby enhancing ESG performance and contributing to the realization of green development.

Second, the government should increase support for the development of intelligent manufacturing in non-state-owned enterprises, including technology upgrades and talent cultivation, and adopt differentiated policies for firms in different industries to promote the comprehensive advancement of intelligent manufacturing.

Third, firms should strengthen friendly interaction and communication with the government and relevant departments, establish a sound government-business relationship, and jointly create a favourable environment for the development of intelligent manufacturing.

Author Contributions

Conceptualization, Mu Zhang; methodology, Mu Zhang; validation, Mu Zhang, Yan Li and Wangjing Xu; formal analysis, Mu Zhang and Yan Li; investigation, Wangjing Xu; resources, Mu Zhang; data curation, Mu Zhang, Yan Li and Wangjing Xu; writing—original draft preparation, Mu Zhang and Wangjing Xu; writing—review and editing, Mu Zhang and Yan Li; supervision, Mu Zhang; project administration, Mu Zhang; funding acquisition, Mu Zhang. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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