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Digital Transformation, Manufacturing Total Factor Productivity and Green Technology Innovation

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Abstract: This study investigates the dynamic relationship between digital transformation and green technology innovation in China's manufacturing sector, with a focus on the mediating role of total factor productivity. Based on the panel data of A-share listed manufacturing enterprises in Shanghai and Shenzhen from 2010 to 2022, it is found that the digital transformation of manufacturing industry significantly promotes green technological innovation, and total factor productivity plays an important mediating role in it. Specifically, digital transformation provides strong support for green technology innovation by optimising resource allocation and improving production efficiency. Heterogeneity analyses show that large enterprises and state-owned enterprises (SOEs) perform more significantly in the promotion of green technology innovation by digital transformation. The findings provide a new perspective for understanding the intrinsic connection between digital transformation and green technology innovation in the manufacturing industry, as well as policy insights for promoting high-quality development of the manufacturing industry and achieving green development.

Keywords: digital transformation of manufacturing, green technology innovation, total factor productivity, mediating effect

1. Introduction

The digital economy drives global growth by integrating advanced technologies like AI and IoT into traditional industries, enabling manufacturing digital transformation through smart production and supply chain optimization [1]. Concurrently, green development has emerged as a vital national strategy, particularly for manufacturing's resource-intensive sector. Green innovation reduces emissions while creating eco-friendly products, enhancing both corporate sustainability and China's carbon neutrality goals [2]. Total factor productivity, reflecting efficiency gains from technological advancement, remains crucial for measuring economic quality [3]. These dual forces of digitalization and green innovation synergistically propel manufacturing upgrades and sustainable development. With the booming development of digital economy, enterprise digital transformation has become the key to enhance competitiveness and achieve sustainable development. Many scholars have deeply explored its impact on green technology innovation, trying to reveal the relationship between the two and the mechanism of action.

Using a sample of A - share listed companies in Shanghai and Shenzhen from 2010 - 2021, Han - You Xu and Yi - Fei Xu [4] found digital transformation is positively linked to firm value, creating

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value via green tech innovation. Substantive green innovation mediates, while strategic green innovation has no value effect. The mediation is more significant in the east and high - regulatory regions. Yang Renfa [5] studied digital tech innovation's impact on corporate ESG performance. It enhances ESG performance through three channels: increasing market value, promoting green transformation, and reducing information asymmetry. Song Deyong et al. [6] found digital tech application improved enterprise total factor productivity, solving the digital - era "Solow's paradox" after endogeneity and robustness tests. Liu Zhiming [7] said digital transformation boosts enterprise green tech innovation, more so for SOEs and high - tech firms. Wang Tingting et al. [8] showed a significant inverted "U" relationship between manufacturing enterprises' digitalisation and green tech innovation.

Existing literature lacks consensus on digital transformation's impact on corporate green tech innovation. Despite proposed mechanisms like information sharing, further analysis is needed.

This paper explores the manufacturing industry's digital transformation impact on green tech innovation, focusing on total factor productivity's mediating role. It constructs a multiple - regression model to examine the direct impact and the intermediary role, enriching relevant research. By mediation - effect analysis, it reveals that digital transformation promotes green tech innovation by enhancing total factor productivity.

2. Theoretical analysis and research hypothesis

2.1. Digital transformation of manufacturing industry and green technology innovation

The digital transformation of manufacturing means manufacturing enterprises use digital technologies like big data, AI, and IoT to comprehensively upgrade production processes, management and business models. This can support green technology innovation in multiple ways [9].

On one hand, digital tech enables fine - grained production - process management. Installing sensors on equipment allows enterprises to collect real - time data on energy consumption, raw - material usage, and pollutant emissions. Big - data analysis of this data helps identify production - process energy waste and pollution issues, enabling targeted green - tech innovation [10]. On the other hand, digital transformation promotes collaborative innovation among enterprises [11]. On digital platforms, manufacturing firms can share info and integrate resources with upstream/downstream enterprises, research institutes, and universities. This model breaks tech barriers between enterprises and speeds up green - tech dissemination and application. New quality productivity promotes the "quantity - increasing and quality - improving" green innovation of manufacturing enterprises, and digital transformation is an important way for it to do so [12]. For example, with digital transformation, manufacturing enterprises can jointly develop more eco - friendly raw - material substitution plans and share usage data with suppliers; in green - tech innovation, they can use their R & D strength to cooperate with research institutions to solve problems and progress [13].

H1: Digital transformation in manufacturing can facilitate green technology innovation.

2.2. Digital Transformation, Total Factor Productivity and Green Technology Innovation in the Manufacturing Industry

Total factor productivity (TFP) is the extra production efficiency when production - factor input levels are fixed. The manufacturing industry's digital transformation notably boosts total factor productivity. Digital - technology R & D innovation cuts production - link waste and redundancy, optimising the process and enhancing enterprise productivity [14]. Meanwhile, digital tech improves enterprise management. For example, with the enterprise resource planning (ERP) system, enterprises can

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optimally allocate human, material, and financial resources, increasing resource - use efficiency and promoting total factor productivity [15].

When total factor productivity rises, enterprises are more motivated and capable of green - technology innovation [16]. Firstly, higher TFP means stronger economic strength, allowing more investment in green - technology R & D and equipment renewal [17]. Secondly, increased TFP indicates improved productivity and management. Enterprises can better integrate internal and external resources, attract top talents and advanced technologies, creating good conditions for green - technology innovation.

H2: Digital transformation in manufacturing facilitates green technology innovation through total factor productivity enhancement.

3. Variable Selection and Model Setting

3.1. Sample Selection and Data Sources

This paper samples Shanghai and Shenzhen A - share listed manufacturing enterprises from 2010 - 2022. Around 2010, China's capital market matured, with better - disclosed corporate information and higher - quality data. By the study, 2022 data were well - collated and audited, ensuring completeness and accuracy.

Raw data were processed as follows: (1) Exclude ST and *ST enterprises; (2) Shrink - tail continuous variables at 1% and 99% to reduce extreme - value interference; (3) Delete seriously anomalous samples. Finally, 6885 high - quality sample sets were obtained. Data mainly came from CSMAR, China Energy Statistics Yearbook, and CNRDS databases. Subsequently, STATA17.0 was used for analysis.

3.2. Definition of variables

(1) Explained variable: green technology innovation

Green tech innovation aims to save energy and reduce emissions through process and resource - utilization improvements [18]. It's measured in three main ways: data envelopment analysis [19], comprehensive - indicator system [20], and single - indicator measurement. Considering indicator - construction and data - availability, based on Wang Xin et al. [21], this study measures green - tech innovation in advanced manufacturing by the natural logarithm of the sum of green inventions and utility models reported by listed firms that year, plus 1. As the number of self - filed green inventions that year is less used, it's used for robustness tests.

(2) Explanatory variable: digital transformation

In this paper, we refer to Wu Fei et al. [22] to construct the enterprise digital - transformation measurement index. The word - frequency - based method is widely used in digital - transformation research. An enterprise's annual - report vocabulary reflects its strategy. We identify digital - related keywords from five aspects: AI, big data, blockchain, cloud computing, and digital - tech application. Then, we use Python to build assessment indicators based on keyword - aggregation frequency for text mining and word - frequency analysis. Due to the right - skewed sample data, we use the method of adding 1 and taking the natural logarithm for data standardisation.

(3) Mediating variable: total factor productivity

Total factor productivity (TFP) is a key enterprise productivity metric. Referring to Lu et al. [23], we calculate TFP using the LP method with the Cobb - Douglas production function.

(4) Control variables

The control variables selected in this study are rigorously screened to eliminate confounding factors.

Table 1: Variable types, names and definitions

typology	name (of a thing)	notation	define
explanatory variable	Green Technology Innovation	GI	The natural logarithm of the sum of the number of green inventions independently filed in the year and the number of green utility models independently filed in the year plus 1
explanatory variable	Digital Transformation	DCG	Natural logarithm of the frequency of digitisation-related keywords in the annual report plus 1
intermediary variable	Total factor productivity	TCP	The LP method was used to measure
control variable	Enterprise size	Size	Natural logarithm of total assets for the year
	Age of business	Age	Natural logarithm of the year of study minus the year of listing
	gearing	Lev	Total liabilities at year-end divided by total assets at year-end
	return on assets	ROA	Net profit divided by net assets
	Enterprise growth	Growth	Year-on-year growth rate of operating income
	Fixed assets as a percentage	Fix	Ratio of net fixed assets to total assets
	shareholding concentration	Top1	Number of shares held by the largest shareholder/total number of shares
	two jobs in one	Dual	The chairman of the board of directors is also the general manager take 1, otherwise 0
	Board size	Board	Natural logarithm of the number of board members

3.3. Modelling

In order to test the impact of digital transformation of manufacturing industry on green technology innovation of enterprises, the following empirical model is established:

$$GI_{i,t} = \alpha_0 + \alpha_1 DCG_{i,t} + \alpha_2 \, Controls_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{1}$$

Meanwhile, in order to further verify the role of digital transformation on enterprise innovation output under the influence of mediation effect, the empirical model is established as follows: (2) is the impact of digital transformation of manufacturing industry on enterprise total factor productivity, and (3) is the impact of enterprise total factor productivity on enterprise green technology innovation.

$$TCP_{i,t} = \beta_0 + \beta_1 DCG_{i,t} + \beta_2 \, Controls_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{2}$$

$$GI_{i,t} = \gamma_0 + \gamma_1 TCP_{i,t} + \gamma_2 DCG_{i,t} + \gamma_3 \, Controls_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{3}$$

Where GI is the explanatory variable, i.e. green technological innovation of enterprises, which is the sum of the number of green inventions independently filed in the year and the number of green utility models independently filed in the year plus 1 to take the logarithm. DCG is the explanatory variable, which indicates the degree of digital transformation. Controls denote the control variables, andα_0 ,β_0 ,γ_0 are the constant terms.

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4. Empirical analysis

4.1. Descriptive statistics of variables

From Table 2 data, the green technology innovation (GI) index of A - share listed manufacturing firms varies greatly. GI's min is 0, max is 4.170, mean is 0.480, and std dev is 0.940. This shows uneven green - tech - innovation development among China's listed manufacturing enterprises, with some having significant results and others few activities. For explanatory variables, the digital transformation level (DCG) of the manufacturing industry has similar unevenness. DCG's min is 0, max is 4.600, and std dev is 1.240, indicating large differences in digital - transformation advancement among firms. Enterprise total factor productivity (TFP) is more concentrated, but the std dev shows some fluctuations among enterprises, reflecting differences in production efficiency.

Table 2: Descriptive statistics of variables

Variable	N	Mean	SD	Min	p50	Max
GI	6885	0.480	0.940	0	0	4.170
DCG	6885	1.110	1.240	0	0.690	4.600
TFP	6885	8.640	1.080	4.370	8.590	11.85
Size	6885	22.59	1.330	19.69	22.46	26.15
Age	6885	2.970	0.330	0.920	3	4.020
Lev	6885	0.480	0.200	0.0700	0.480	0.990
Growth	6885	0.260	0.800	-0.710	0.0900	5.960
Fix	6885	0.250	0.150	0.0200	0.210	0.720
Dual	6885	0.170	0.380	0	0	1
Board	6885	2.170	0.190	1.610	2.200	2.710
ROA	6885	0.0300	0.0700	-0.270	0.0300	0.220
Top1	6885	33.75	14.45	8.410	30.95	72.96

4.2. Baseline regression analysis

Based on 2010 - 2022 panel data of Chinese manufacturing firms, a multiple regression model is built and measured, with results in Table 3. Results show manufacturing digital transformation can significantly boost enterprises' green tech innovation, in line with previous theoretical expectations. It offers new impetus and path for green tech innovation by optimizing resource allocation, enhancing info - processing efficiency and promoting tech integration. Digital tech creates favorable conditions for green tech innovation by achieving refined production management, cutting waste and consumption. Digital transformation also promotes green tech innovation by facilitating knowledge sharing and tech diffusion, accelerating the connection between enterprises and external innovation resources. H1 is verified.

Table 3: Benchmark regression results, robustness test results and Mediating effect test results

	Benchmark regression	Robustness test	Mediating effect test	
			TFP	GI
	GI	LnInva	(1)	(2)
DCG	0.0389 ***	0.0595 ***	0.0582 ***	0.0350 ***
	(0.0105)	(0.00935)	(0.00624)	(0.0106)
Size	0.240 ***	0.223 ***	0.596 ***	0.200 ***
	(0.00985)	(0.00878)	(0.00586)	(0.0156)

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Table 3: (continued).

Age	-0.156 ***	-0.119 ***	0.116 ***	-0.164 ***
	(0.0375)	(0.0334)	(0.0223)	(0.0375)
Lev	0.200 ***	0.128**	0.638 ***	0.157**
	(0.0620)	(0.0553)	(0.0369)	(0.0633)
Growth	0.00869	0.00964	-0.0553 ***	0.0124
	(0.0129)	(0.0115)	(0.00769)	(0.0130)
Fix	-0.0985	-0.139*	-1.003 ***	-0.0310
	(0.0807)	(0.0719)	(0.0480)	(0.0832)
Dual	0.0561**	0.0973 ***	-0.0449 ***	0.0591**
	(0.0270)	(0.0240)	(0.0160)	(0.0270)
Board	0.338 ***	0.243 ***	0.00854	0.338 ***
	(0.0561)	(0.0500)	(0.0333)	(0.0560)
ROA	0.330*	0.265*	2.851 ***	0.138
	(0.172)	(0.154)	(0.102)	(0.182)
Top1	-0.00480 ***	-0.00446 ***	0.00467 ***	-0.00512 ***
	(0.000764)	(0.000681)	(0.000454)	(0.000769)
Year	Yes	Yes	Yes	
Ind	Yes	Yes	Yes	
_cons	-5.027 ***	-4.574 ***		0.0673 ***
	(0.309)	(0.276)		(0.0204)
N	6885	6885	-5.601***	-4.650 ***
R2	0.254	0.245	(0.184)	(0.329)
adj. R2	0.246	0.237	6885	6885

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

4.3. Robustness Tests

This study measures the green technological innovation of the advanced manufacturing industry in baseline regression. Given indicator - construction and data - availability requirements, it uses the natural logarithm of the sum of the number of green inventions and utility models independently applied for by listed companies in that year, plus 1. Since the number of green inventions independently applied for in that year is less used in related studies, it's taken as a substitute indicator for robustness test. The regression results in Table 3 show that after replacing the measure, the estimated values of the explanatory variables (LnInva and DCG) are consistent, indicating the regression model is robust.

4.4. Tests for mediating effects

Table 3 (1) and (2) show digital transformation positively impacts total factor productivity (coef. 0.0582, 1% sig.), enhancing enterprise productivity. Total factor productivity also significantly (1% sig.) and positively affects green tech innovation (coef. 0.0673), suggesting digital transformation improves production efficiency as an intermediary. Digital transformation directly and significantly (1% sig.) impacts green tech innovation (coef. 0.0350), promoting it through efficiency gains, alongside indirect promotion. This validates its dual - action in enterprise innovation and productivity growth.

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4.5. Heterogeneity analysis

(1) Analysis of firm size heterogeneity

In the firm - size heterogeneity test, large firms' digital transformation more significantly contributes to green tech innovation. After a significant Chow - test result for inter - group coefficient differences, specifically, large enterprises' digital transformation regression coefficient is 0.0397 (1% sig.), while that of SMEs is 0.0355 (1% sig.), but lower. This may be because large enterprises have stronger resource - integration capabilities and economies of scale in digital transformation, enabling more efficient application of digital technologies to green innovation.

(2) Analysis of the heterogeneity of business ownership

This study analyzes business - ownership heterogeneity. Test results show significant inter - group differences and a significant Chow - test outcome. Data indicate that state - owned enterprises' (SOEs) digital transformation has a more prominent green - tech - innovation - driven effect. The regression coefficient for SOEs is 0.0432 (1% sig.), while that for non - SOEs is 0.0367 (5% sig.). This may be due to SOEs' special endowment.

Table 4: Heterogeneity test results for panel data

	state-owned business	non-state enterprise	big business	small and medium enterprise
	(1)	(2)	(3)	(4)
	GI	GI	GI	GI
DCG	0.0432 ***	0.0367**	0.0397 ***	0.0355 ***
	(0.0136)	(0.0158)	(0.0139)	(0.0126)
Year	Yes			
Ind	Yes			
_cons	-5.113 ***	-5.580 ***	-6.985 ***	-1.655 ***
	(0.365)	(0.431)	(0.953)	(0.420)
N	4772	2113	4850	2035
R2	0.249	0.350	0.270	0.161
adj. R2	0.238	0.328	0.260	0.132

5. Conclusions, Insights and Outlook

5.1. Conclusions of the study

This paper reveals that the manufacturing industry's digital transformation significantly promotes firms' green innovation output, with results proven robust by regression and relevant tests. Total factor productivity mediates this relationship, as digital transformation boosts company productivity for enhanced green tech innovation. Large - scale manufacturing and state - owned enterprises see a more pronounced promoting effect from digital transformation on green innovation compared to SMEs and non - state - owned ones.

Digital - transformation - driven green innovation gives enterprises new ideas and backs the national green strategy. It's an all - around corporate shift, not just tech - centric. By aligning with policies, enterprises can achieve eco - economic wins. They should own their role and integrate digital transformation into long - term strategies. Digital tech is key for green change, slashing energy and emissions via data management. Seek external synergy to cut R & D costs and speed up green tech. The government should guide and support manufacturers' digital and green efforts. Use incentives for R & D, build infrastructure, and strengthen supervision on data and innovation. Enterprises should

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cultivate talents through university - firm cooperation and internal training. Take social responsibility, embed green ideas in culture, and boost social recognition via reports.

Overall, this green innovation benefits both enterprises and the national green strategy. With government policy improvement and joint efforts, we can contribute to carbon goals and high - quality manufacturing development.

5.2. Outlook

This paper has research results on digital transformation's impact on green tech innovation in manufacturing, yet limitations exist. The sample mainly covers 2010 - 2022 A - share listed firms, lacking non - listed ones. Future research can expand the sample. The econometric model is simple, future work could explore complex models to better analyze the causal relationship.

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