Digital Transformation and Green Total Factor Productivity of Chinese Listed Companies: Evidence from Academic Perspective

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Abstract. Digital transformation and green total factor productivity are important measures to implement the dual carbon strategy and promote the high-quality development of enterprises. Based on micro-level data from listed companies from 2011 to 2021 and matched with text data containing digitalization keywords, this article examines the effects of corporate digital transformation on green total factor productivity. The study found that digital transformation significantly improves the green total factor productivity of enterprises, and this result holds even after robustness tests and the inclusion of control variables such as variable substitution, fixed effects interaction, double-cluster robust standard errors, and added control variables. The research in this article enriches the study on the economic consequences of digital transformation for real-world enterprises and the factors influencing green total factor productivity of enterprises. It provides valuable references for driving enterprises from traditional factor-driven to innovation-driven approaches based on green orientation.

Keywords: digital transformation, green total factor productivity, financial constraints, green innovation.

1. Introduction

Since the 20th National Congress of the Communist Party of China, our country has proposed the strategic guideline of "promoting ecological priority, intensive and efficient utilization, and green and low-carbon development." The consensus of promoting harmonious coexistence between humans and nature is established, making environmental protection a critical element in development. Green total factor productivity, as an important indicator of measuring green economic development, incorporates energy and environment into the traditional total factor productivity model, which helps balance the contradiction between economic development and ecological civilization (Gu et al., 2022; Li & Chen, 2019). Existing research has indicated that factors such as industrial agglomeration (Bao & Peng, 2023), environmental regulations (Hu & Ding, 2020), openness to foreign countries (Cui & Lin, 2019), and green finance (Zhang & Hui, 2023) have an impact on the green total factor productivity of enterprises. Furthermore, Dai & Luo (2022) have identified the promoting effects and influencing mechanisms of environmental regulations and government technological support on the green total factor productivity of the industrial sector. Liu et al. (2022) and Li et al. (2021) have examined the changes in green total factor productivity of enterprises in heavily polluting and high-tech industries, respectively. Therefore, an in-depth exploration of the incentive factors of enterprise green total factor productivity holds significant practical implications for facilitating sustainable development and high-quality economic growth of enterprises.

In recent years, with the emergence and application of digital technologies, traditional business models have been significantly disrupted while providing new ideas for the sustainable development of enterprises (Lyu et al., 2022; Liu & Peng, 2023). Enterprise digital transformation refers to how enterprises comprehensively utilize new digital technologies such as big data, artificial intelligence, and cloud computing and integrate them into their daily operations (Vial, 2019; Wu et al., 2021). There has been a considerable amount of literature discussing the economic effects of enterprise digital transformation. Specifically, firstly, digital transformation reduces operational costs by influencing audit pricing (Zhang et al., 2021) and debt default risk (Wang et al., 2022). Secondly, digital transformation improves organizational performance (Hu, 2020) and enterprise value (Huang et al., 2021) by enhancing the level of specialization and production efficiency (Yuan et al., 2021; Ji et al., 2023). A small portion of the literature has discussed the environmental effects of enterprise digital transformation, such as how it promotes corporate social responsibility (Xiao et al., 2021; Zhao, 2022) and compliance with ESG standards (Fang et al., 2023; Hu et al., 2023), as well as reduces corporate carbon emissions through technological progress (Yang et al., 2023; Ma & Yang, 2023). Therefore, with the widespread implementation of the "dual carbon" strategy, scholars are paying close attention to how to enhance the sustainable development performance of enterprises through the application of digital technologies.

Most existing studies have shown that digital transformation can effectively enhance enterprise total factor productivity. In terms of external factors, researchers like Hua and Jun (2022) argue that digital transformation mainly improves total factor productivity by alleviating enterprise financing constraints. In terms of internal factors, digital transformation can enhance total factor productivity by improving innovation performance (Zhao et al., 2022), optimizing human capital structure (Zhao et al., 2021), and enhancing internal quality control (Jiang and Zhang, 2023). However, there is currently limited research in the micro-level domain of green total factor productivity. Lei (2022), based on panel data from 30 Chinese provinces from 2012 to 2020, using fixed effects models and threshold models, concludes that digital finance, technological innovation, and their interaction can significantly promote the improvement of green total factor productivity in the circulation industry, with the impact showing a decreasing distribution pattern from east to west. Some limited literature has explored the relationship between digital transformation and green total factor productivity. For example, Liu and Peng (2023), using a sample of A-share listed manufacturing enterprises from 2011 to 2019, applied the SBM-DDF model to find that digital transformation has a positive impact on green total factor productivity through promoting green technological innovation and strengthening the misallocation of human resources. The impact also exhibits regional differences, with the eastern region showing the most significant improvement, while a company's flexible strategy also influences the effect. Hui (2023), based on panel data of Chinese A-share listed companies from 2009 to 2020, applies the multi-period DID method to conclude that smart city construction can significantly enhance enterprise green total factor productivity. Moreover, the effect of smart city construction is more pronounced in larger firms, non-state-owned enterprises, eastern regions, and areas with lower levels of marketization.

Overall, there is significant room for expansion in the research topics related to digital transformation and green innovation in enterprises. On the one hand, existing research on digital transformation mostly takes a macro perspective. It focuses on the factors influencing the economic effects of enterprise digital transformation, with limited literature on the research topic of green total factor productivity. This provides a potential opportunity to extend the microeconomic consequences of digital transformation further. On the other hand, scholars have mostly explored the external factors affecting green total factor productivity of enterprises from a macro perspective, such as market-oriented and command-oriented environmental regulatory policies, such as industrial structure and market environment (Hui, 2023; Wang et al., 2022). However, the impact of the changing external environment driven by digital transformation development has not been widely researched. Based on this, this study focuses on the micro perspective to explore the relationship and mechanism of action between digital transformation and green innovation in enterprises, aiming to provide a useful supplement to existing research.

The marginal contributions of this article can be summarized in three aspects. Firstly, this article integrates the digital transformation of enterprises and the green total factor productivity (GTFP) into the same analytical framework, attempting to explore the microeconomic consequences of digital transformation from the perspective of the enterprise's GTFP and expanding the existing research. Secondly, using the sample of A-share listed companies in the Shanghai and Shenzhen stock markets from 2011 to 2021, this article provides empirical evidence for the enhancing effects and mechanisms of digital transformation on the enterprise's GTFP, which can help enterprises adopt differentiated and dynamic strategies in the practice of digital transformation, balancing economic benefits and social benefits. Thirdly, this article reveals that alleviating financing constraints and accelerating green innovation are mechanisms for digital transformation to improve the enterprise's GTFP.

2. Literature Review and Theoretical Mechanism

Based on theories and existing literature, digital transformation has a positive impact on the green total factor productivity of enterprises (Gu et al., 2022). However, it is worth noting that improving green total factor productivity is a complex process involving processes such as raw material storage, product production, and wastewater treatment (Liu & Peng, 2023). Furthermore, digital transformation primarily enhances the green total factor productivity of enterprises by accelerating green innovation and alleviating financing constraints.

Firstly, the digital transformation of enterprises can optimize internal management and enhance control over supply chains, thereby adjusting the allocation of enterprise resources, promoting increased investment in innovative resources, and ultimately improving green total factor productivity (Huang et al., 2021). Digital transformation not only requires enterprises to transform their business models and processes, proposing better models to replace existing ones, but also involves changing organizational models. Relying solely on business reshaping is difficult to achieve digital transformation for enterprises (Xia & Lou, 2018). On the other hand, enterprises can flexibly apply digital technologies to production and operations, improving the structure of input factors. These technologies can optimize the entire internal configuration, ranging from input factors to organizational structure. This can effectively reduce the degree of input factor distortion and mismatch, improving resource allocation efficiency (Kunkel & Matthess, 2020).

In the current stage, the focus of green innovation in enterprises mainly lies in reducing energy consumption, minimizing pollution generation and emissions, as well as adopting new technologies and equipment. This requires enterprises to invest a significant amount of capital in the early stages, leading to a short-term increase in production costs (Lee et al., 2022). Digital transformation enables small and medium-sized enterprises to utilize better the financial services provided by the Internet (Liu et al., 2023), thus reducing information asymmetry between enterprises and capital and alleviating their financing difficulties. Digital transformation can accelerate information sharing and knowledge integration among enterprises, facilitate the dissemination of advanced knowledge and technology within collaborative organizations, and enhance the knowledge supply required for green technological innovation in enterprises (Ma & Yang, 2023). Furthermore, the application of digital technologies reduces transaction costs for enterprises, leading to economies of scale and network effects, which drive enterprises to fulfill their environmental responsibilities actively. It can shape a positive corporate image, stimulate green consumption by customers, and bring more intangible resources to enterprises, thereby improving green total factor productivity (Wang & Li, 2021).

Thirdly, due to the cautious attitude of financial institutions towards credit risk control, small and medium-sized enterprises (SMEs) are more likely to be neglected and excluded by financial institutions compared to large enterprises, resulting in a scarcity of funds and the expansion of financing constraints (Nie et al., 2021). However, digital transformation provides a new approach for SMEs to alleviate financing constraints. Firstly, as a key direction of the construction of Digital China, the digital transformation is supported by government subsidies to relieve the market financing pressure for enterprises (Zhao Chenyu et al., 2021). Secondly, digital transformation releases enterprise human resources, improves business processes, and enhances information disclosure. By leveraging digital technologies, enterprises can effectively improve the integrity and effectiveness of information disclosure, thus attracting investors and reducing information asymmetry issues in the financing process, thereby alleviating financing constraints (Hua Junguo et al., 2022). With reduced constraints on financing, enterprises have sufficient funds, strengthening their willingness to invest in research and development and green development transformation, further promoting the development of green total factor productivity. Therefore, it is hypothesized in this study that:

H: The digital transformation enhances the green total factor productivity of enterprises by accelerating green innovation and alleviating financing constraints.

3. Indicator Construction, Data Sources, and Identification Strategies

3.1. Indicator Construction

3.1.1. Selection of dependent variables

Compared to traditional total factor productivity indicators, green total factor productivity considers the environmental cost of economic development. It provides a more comprehensive assessment of the achievements of sustainable development for enterprises. According to the existing literature (Meng & Zhao, 2022; Li et al., 2021), this study chooses the non-directional, variable returns to scale SBM-DDF model. Regarding input variables, considering the production function and data availability, this study selects three variables: labor, capital, and energy. Labor input is measured by the number of "employees at the end of the year" in the enterprise; capital input is measured by the total fixed assets of the enterprise (Wu et al., 2022); energy input is the standardized coal equivalent quantity of different energy inputs in the enterprise. Taking into account the differences between different types of energy in the production process, this study converts the energy input of the enterprise into standardized coal based on the conversion coefficients provided by the "Comprehensive Energy Consumption Calculation Rules" of the People's Republic of China (Li et al., 2023). Output variables are divided into expected output and unexpected output. The operating income of the enterprise measures the expected output. The unexpected output is measured by the amount of industrial waste generated by the enterprise, including industrial SO_2 emissions, industrial dust emissions, and industrial wastewater emissions, following the approach of Cui Xinghua and Lin Mingyu (2019).

3.1.2. Selection of independent variables

This study draws on existing research (Zhou & Li, 2023; Li et al., 2022; Wu Fei et al., 2021) and applies the textual analysis method, employing text-mining techniques to measure the level of digital transformation in Chinese listed companies' annual reports through the proportion or frequency of keywords related to "digitization." This measure is referred to as DIGT.

Digital transformation of enterprises is a significant strategic initiative for the high-quality development of businesses today, and it is more easily reflected in the comprehensive and guiding annual reports of companies. The vocabulary usage in annual reports reflects the company's strategy and embodies its business philosophy and development path. This paper measures the degree of digital transformation of companies by conducting word frequency analysis on the annual reports of listed companies related to digital transformation. The specific approach is as follows: First, this paper uses Python web scraping functionality to obtain and organize the annual reports of all A-share listed companies in the Shanghai Stock Exchange and Shenzhen Stock Exchange. Then, using the Java PDFbox library, all text content is extracted. Second, based on the five aspects of "application of underlying technologies" (including artificial intelligence, big data, cloud computing, blockchain) and "application of digital technologies," key terms related to digital transformation in the annual reports of listed companies are extracted. Finally, the Jieba functionality is used to tokenize all samples and form a data pool. Based on the collected key terms, a search, match, and word count are performed to generate an aggregated word spectrum. The natural logarithm of the aggregated word spectrum plus one is used as an indicator for the digital transformation of listed companies, denoted as DIGT. The higher the DIGT value, the higher the degree of digital transformation for the entity company.

3.1.3. Selection of Mechanism Variables

Financing Constraints. Referring to existing studies (Ding et al., 2022; Pan et al., 2019), we use the KZ index to measure financing constraints. Considering five financial indicators, including operating net cash flow, cash dividends, cash holdings, leverage ratio, and Tobin's Q, we perform relevant processing. Firstly, we compare each indicator with its median and set up dummy variables, which are summed to obtain the KZ index. Secondly, we employ ordered logistic regression to regress the KZ index as the dependent variable on the absolute values of the above five indicators. By doing so, we obtain the regression coefficients for each variable. Lastly, using the estimation results of the regression model, we calculate the KZ index for each listed company in the historical years. A larger KZ index indicates a more severe financing constraint the company faces.

Green Innovation. This study refers to existing research (Qi et al., 2018; Wang et al., 2023; Xu & Cui, 2020) and relies on the Green Patent Classification List and International Classification Codes released by the World Intellectual Property Organization (WIPO) in 2010. These are matched with the classification numbers in the patent data from the Chinese National Intellectual Property Administration to identify the number of green patent applications by listed companies. In the empirical testing process, this variable is transformed by adding one and taking the natural logarithm. A higher value indicates a higher level of green innovation for the company, denoted as GRI.

3.2. Model design

Based on the previous theoretical analysis and existing literature research, we first build the benchmark measurement model:

In equation (1), $GTFP_{it}$ represents the green total factor productivity level of firm i in period t, while $DIGT_{it}$ represents the level of digital transformation of firm i in period t. In order to address the issue of omitted variable bias, this study introduces control variables (Z_{it}) including firm size (size), measured as the logarithm of total assets; firm age (age), measured as the logarithm of years since establishment; firm profitability (roa), measured as net profit/total assets; firm growth capability (growth), measured as the growth rate of total assets; board size (board), measured as the logarithm of the number of board members; ownership concentration (top3), measured as the proportion of shareholding by the top three shareholders; independent director ratio (indtor), measured as the proportion of independent directors to the total number of directors; fixed asset ratio (fixratio), measured as net fixed assets/total assets; and managerial duality (duality), measured as the extent of overlap between the roles of chairman of the board and CEO. Moreover, to account for individual heterogeneity within groups, the model includes firm-specific fixed effects denoted by μ_i, industry fixed effects denoted by γ_j, and time fixed effects denoted by δ_t. Additionally, this study clusters the error term $\varepsilon_{i,t}$ at the firm level to address the issue of systematic heteroscedasticity in the model.

3.3. Data sources and descriptive statistics

The research selected the A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2011 to 2021 as the research objects, and performed screening according to the following steps: (1) excluding financial companies; (2) excluding samples with missing financial data or those with liabilities exceeding assets; (3) excluding samples marked as ST or *ST in the current year. Clustering regression was conducted at the company level to eliminate the interference of intergroup differences in data and reasonably control the impact of heteroscedasticity. The financial data used in the study were sourced from the CSMAR database.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
DIGT	28914	1.356	1.376	0.000	4.927
GTFP	28914	8.464	1.061	5.480	11.145
size	28914	22.223	1.342	15.573	28.624
age	28914	2.840	0.363	0.000	4.143
roa	28914	0.042	0.122	-1.683	10.032
growth	28914	0.580	29.588	-0.972	4719.612
board	28914	2.125	0.200	1.099	2.890
top3	28914	34.234	15.009	0.286	89.991
indtor	28914	0.376	0.056	0.143	0.800
fixratio	28914	0.210	0.160	0.000	0.941
duality	28914	0.287	0.453	0.000	1.000
cash	28914	0.198	0.141	0.000	1.000
loss	28914	0.105	0.307	0.000	1.000

4. Empirical Analysis

4.1. Benchmark Regression

Table 2. Benchmark regression

	(1)	(2)	(3)	(4)
	OLS		Fixed effect model	
DIGT	0.099***	0.032***	0.093***	0.027***
	(0.005)	(0.003)	(0.005)	(0.004)
size		0.626***		0.532***
		(0.003)		(0.008)
age		0.035***		0.272***
		(0.010)		(0.033)
roa		0.478***		0.297***
		(0.098)		(0.090)
growth		0.000		-0.000
		(0.000)		(0.000)
board		-0.048**		0.058**
		(0.023)		(0.027)
top3		0.003***		0.001
		(0.000)		(0.000)
indtor		-0.439***		0.180**
		(0.081)		(0.076)
fixratio		-1.191***		-1.110***
		(0.026)		(0.045)
duality		-0.044***		-0.002
		(0.008)		(0.006)
_cons	8.329***	-5.173***	8.346***	-4.158***
	(0.009)	(0.086)	(0.007)	(0.205)
Firm FE	N	N	Y	Y
Year FE	N	N	Y	Y
Industry FE	N	N	Y	Y
N	28914	28914	28397	28397
adj. R^2	0.016	0.667	0.850	0.908

Table 2 presents the regression results of the relationship between digital transformation and green total factor productivity. Columns (1) and (2) report the results of OLS models. Regardless of the inclusion of control variables, DIGT is significantly positive at the 1% level. Columns (3) and (4) report the results of fixed effects models. The results still show that DIGT is significantly positive at the 1% level, regardless of the inclusion of control variables. Therefore, the research hypothesis is validated, indicating that digital transformation enhances firms' green total factor productivity. In economic terms, a one percentage point increase in digital transformation leads to a 0.027 increase in green total factor productivity for the firm. From the perspective of control variables, firms with the larger size, longer establishment years, higher profitability, and higher ownership concentration also tend to have higher levels of green total factor productivity.

4.2. Robust analysis

4.2.1. Variable substitution

We are replacing the variable level of digital transformation in enterprises. In the previous section, we used the calculation method of Wu Fei et al. (2021), whereas, in this section, we adopt the approach of Zhao Chenyu, Wang Wenchun, and Li Xuesong (2021) to statistically analyze the frequency of 99 digital-related terms in four dimensions: digital technology application, internet business models, intelligent manufacturing, and modern information systems. By doing so, we reconstruct the index of the degree of digitalization in enterprises. The specific results are shown in column (1) of Table 3. The results indicate that even after replacing the measurement method for digital transformation, it still significantly promotes the green total factor productivity of enterprises.

4.2.2. Panel interaction with fixed effects

Industries with high technological capabilities or cities with advanced economic development will likely have relatively well-developed digital infrastructure. They are more advantaged in the development of digital technology innovation (Wang et al.,2023). Based on this, this article introduces fixed effects for the interaction of industry and year, as well as city and year, to control for the impact of factors that vary with the year at the industry and city levels, thereby mitigating the macroeconomic environment changes caused by the development of the digital economy. The robustness test results in columns (2) and (3) of Table 3 show that the coefficient of DIGT is significantly positive, consistent with the benchmark results.

4.2.3. The double-clustered robust standard errors

Considering the intrinsic correlation between different enterprises, we employ a dual clustering adjustment in both individual and time dimensions to overcome the impact of issues such as autocorrelation and heteroscedasticity on statistical inference (Zhang & Li, 2023). The results, as shown in column (4) of Table 3, remain consistent with the benchmark results. The coefficients of the core explanatory variables are still significantly positive.

4.2.4. Increase control variables

To alleviate estimation bias caused by omitted variables, this study incorporates the following variables again: Cash, which is calculated as (monetary fund's + trading financial assets)/ total assets, and loss=1 if net profit is negative in the current year, and 0 otherwise. The results, as shown in column (5) of Table 4, still exhibit significant positive coefficients for the core explanatory variables, consistent with the baseline results.

4.2.5. Endurance analysis

Despite controlling for firm-level control variables and including fixed effects of different dimensions in the model, there may still be omitted variable bias in this study. To address endogeneity issues due to reverse causality and omitted variables, this study employs a two-stage least squares (2SLS) estimation using instrumental variables. In selecting the instrumental variables, this study draws on the practices of previous literature and chooses industry-level digital transformation indices as instrumental variables for regression analysis.

Table 3. Robustness test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Substitute indicators	Interactive fixed effect		Replace the standard error clustering level	Increasing control variables	IV_MEAN	
DIGT2	0.034***						
	(0.008)						
DIGT		0.017***	0.027***	0.027***	0.026***		
		(0.004)	(0.004)	(0.006)	(0.005)		
IV_MEAN						0.065***	
						(0.008)	
size	0.534***	0.530***	0.534***	0.532***	0.522***	0.126***	0.416***
	(0.015)	(0.008)	(0.008)	(0.018)	(0.015)	(0.007)	(0.019)
age	0.284***	0.210***	0.326***	0.272***	0.251***	1.104***	-0.777***
	(0.060)	(0.032)	(0.035)	(0.058)	(0.058)	(0.028)	(0.145)
roa	0.291***	0.267***	0.261***	0.297**	0.180***	-0.033	0.323***
	(0.093)	(0.083)	(0.087)	(0.115)	(0.069)	(0.026)	(0.030)
growth	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
board	0.059	0.038	0.067**	0.058	0.061	0.029	0.048
	(0.042)	(0.026)	(0.029)	(0.039)	(0.041)	(0.035)	(0.042)
top3	0.001	0.001***	0.001	0.001	0.000	-0.002***	0.003***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
indtor	0.174	0.097	0.186**	0.180	0.182*	-0.085	0.276**
	(0.112)	(0.075)	(0.082)	(0.114)	(0.109)	(0.105)	(0.121)
fixratio	-1.120***	-1.105***	-1.147***	-1.110***	-1.139***	-0.315***	-0.858***
	(0.077)	(0.043)	(0.046)	(0.082)	(0.079)	(0.043)	(0.068)
duality	-0.003	-0.002	-0.007	-0.002	-0.002	0.010	-0.015
	(0.009)	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)	(0.011)
cash					-0.197***		
					(0.050)		
loss					-0.158***		
					(0.014)		
_cons	-4.243***	-3.878***	-4.372***	-4.158***	-3.812***		
	(0.369)	(0.205)	(0.219)	(0.381)	(0.375)		
Anderson LM							59.204***
Wald F							59.324***
10% Stock-Yogo						16.38	
Firm FE	Y	Y	Y	Y	Y		
Year FE	Y	Y	Y	Y	Y		
Industry FE	Y	Y	Y	Y	Y		
*Industry*Year FE*		Y					
*City*Year FE*			Y				
N	27828	28339	27483	28397	28397	27685	27685
adj. R^2	0.907	0.914	0.911	0.908	0.910		

This study adopts the mean of the digitization transformation index, which is divided by year-industry (IV_Mean), as an instrumental variable to address endogeneity, drawing inspiration from existing research (Zhou et al., 2022; Xiao et al., 2021). The overall digital transformation of the industry will enhance production efficiency and optimize resource allocation, thereby forcing each firm in the industry to accelerate its digital transformation to adapt to a higher level of industry production. Therefore, the level of digital transformation in the industry as a whole affects the digital transformation performance of individual firms, satisfying the relevance assumption. However, the digital transformation of the industry does not directly influence the green total factor productivity of individual firms, ensuring exogeneity.

Table 3, columns (6) and (7) present the estimation results using instrumental variables. The 2SLS estimation shows that the first-stage results indicate a significantly positive effect of instrumental variables on digital transformation. In the second-stage estimation, when considering endogeneity issues, the coefficients of the level of digital transformation remain significantly positive at the 1% level, consistent with the baseline estimation results. Additionally, in the tests for weak instrument identification, the p-values for the null hypothesis of "weak instrument identification" are all 0.000, significantly rejecting the null hypothesis. In the tests for weak instrument validity, the Wald F statistic exceeds the critical value at the 10% level of the Stock-Yogo weak identification test. Overall, the above tests confirm the rationale of the chosen instrumental variables and further validate research hypothesis 1.

5. Conclusion

In the era of the digital economy wave, digital transformation has become an important path for enterprises to practice sustainable development and promote green total factor productivity. This article examines the specific impact of digital transformation on corporate green total factor productivity from theoretical and empirical dimensions using data from the listed companies on the Shanghai and Shenzhen Stock Exchanges from 2011 to 2021. The research results show that digital transformation significantly improves corporate green total factor productivity. This still holds after robustness tests such as variable substitution, interactive fixed effects, double-clustered robust standard errors, and control variable additions. Based on the findings of this study, the following suggestions are proposed.

First, actively promote the upgrading of enterprise digital transformation and introduce related policies to create favorable external conditions. Firstly, provide government subsidies and tax incentives for enterprises engaged in digital transformation to mobilize their enthusiasm effectively. Secondly, promote the construction of integrated digital platforms, leverage the role of data production factors, promote rational allocation of resources, and improve enterprise operational efficiency. Thirdly, improve laws and regulations on data protection, enhance market supervision, and create a favorable environment for enterprise digital transformation. Finally, attach importance to the construction of infrastructure such as communication and electronics, promote the "5G+" project, and cultivate a high-quality workforce in information technology to provide basic support for enterprise digital transformation.

Second, pay attention to green development indicators of enterprises and leverage government incentives. On the one hand, when evaluating enterprises, the government should not only focus on conventional indicators such as profitability and credit but also pay more attention to the environmental benefits of enterprises, incorporating green development indicators into enterprise ratings to make them more valued. On the other hand, it provides certain rewards and incentives for enterprises with good green development indicators, such as tax breaks, while imposing penalties such as fines and suspending operations on enterprises with significant pollution.

Third, enterprises should respond to the national call for digital transformation and actively engage in green development. Firstly, actively introduce digital technologies and high-level talents to promote internal production and operation reforms within enterprises and unleash their creativity.

Secondly, it relies on innovation to improve production efficiency and develop green enterprises. Enterprises should start from their core businesses and gradually expand into packaging and transportation, reducing production pollution and increasing green total factor productivity. Thirdly, make rational use of funds, not unthinkingly allocating them to expand production, but actively carry out green production reforms to improve production efficiency and reduce environmental pollution, comprehensively enhancing green total factor productivity.

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