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Digital Technology Innovation Empowers Green Transformation and Upgrading of Manufacturing Industry

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Abstract

The manufacturing industry is the backbone of the national economy and one of the major sources of energy consumption and environmental pollution. In the face of the dual challenges of intensifying global warming and increasing scarcity of natural resources, accelerating the green transformation of the manufacturing industry has become a key breakthrough in the implementation of sustainable development strategies. This paper finds that digital technology innovation can effectively promote the green transformation and upgrading of the manufacturing industry, and this result remains robust after a series of robustness tests and endogeneity treatment. Digital technological innovation can reduce transaction costs, enhance human capital and alleviate information asymmetry to a certain extent, and then promote the green transformation and upgrading of the manufacturing industry. Based on the above findings, this paper obtains the following countermeasure suggestions: (1) Strengthen financial support. (2) Formulate policies according to local conditions. (3) Promote cooperation among industries, universities and research institutes.

Keywords

green transformation and upgrading, manufacturing, digital technology innovation, environmental regulation, market concentration

1. Introduction

As an important foundation for the development of the national economy, the manufacturing industry is crucial to promoting high-quality economic development. Made in China 2025 points out that the manufacturing industry should take the road of green development, focus on sustainable development, strengthen green technological innovation, and realize the goal of low-carbon emission reduction. In the context of the "double carbon" goal, in order to meet people's great expectations for a better life, we need to actively cultivate new momentum in the development of the manufacturing industry, and further promote the green transformation and upgrading of the manufacturing industry. However, at present, China's manufacturing industry is big but not strong, big but not excellent, big but not active, and the problem of unbalanced and insufficient regional development of the manufacturing industry has not yet been solved, which seriously affects the high-quality development of the economy. 2023, the scale of China's digital economy exceeded 53.9 trillion yuan, which accounted for 42.8% of GDP, and it has already become a key driving force to improve the quality of the economy and increase efficiency. By incorporating data elements into the production resource allocation system, digital technological innovation significantly improves the process technology level of manufacturing enterprises, reduces operating costs, optimizes production efficiency, and at the same time, strengthens the effectiveness of environmental regulation, providing new technological support for the greening of the manufacturing industry. On the one hand, digital technology innovation provides new solutions for the green transformation of the manufacturing industry. Based on the Internet of Things, big data analysis and other technologies, manufacturing enterprises monitor energy consumption in real time, optimize production processes, and effectively reduce energy consumption and pollutant emissions. On the other hand, the digital platform promotes information sharing and cooperation between upstream and downstream of the industrial chain, helping to build a more transparent and efficient green supply chain system.

In order to promote the green transformation and upgrading of the manufacturing industry, it is particularly crucial to play the role of digital technology innovation. Studies have shown that technological innovation can affect the green transformation and upgrading of the manufacturing industry by improving energy use efficiency, optimizing resource allocation efficiency, and reducing pollutant emissions (Li et al., 2024; Chen, 2024; Bai et al., 2024). With the depth of research, some scholars found that digital technology innovation reduces energy consumption and carbon emissions, which directly affects the green transformation and upgrading of the manufacturing industry (Dong et al., 2023; Li, 2023). Some studies have also focused on the impact of environmental regulation on the green transformation and upgrading of the manufacturing industry. In fact, digital technological innovation can effectively affect the green transformation and upgrading of the manufacturing industry from multiple dimensions, and the variability of market concentration and the degree of environmental regulation may lead to different impacts of digital technological innovation on the green transformation and upgrading of the manufacturing industry. Therefore, it is of great significance to explore the impacts and channels between digital technological innovation and green transformation of manufacturing industry, and to further examine the threshold effect of environmental regulation and the moderating effect of market concentration to promote green transformation and upgrading of manufacturing industry.

2. Literature Review

2.1 Economic Effects of Digital Technology Innovation

Digital technology innovation refers to the process and results of enterprises or organizations relying on digital technologies such as artificial intelligence, blockchain, cloud computing and big data to develop new products, new processes and new business models, etc. (Nambisan et al., 2017). Existing literature has explored the economic effects of digital technology innovation from the perspectives of optimizing resource allocation, improving production efficiency and promoting industrial upgrading. First, the optimization effect of resource allocation. Digital technology improves the efficiency of information circulation and reduces transaction costs by means of artificial intelligence, blockchain, cloud computing and big data, thus promoting the optimization of market mechanisms (Acemoglu & Restrepo, 2018). In addition, digital technology can reduce information asymmetry, enhance the competitiveness of enterprises, and enable a more efficient allocation of capital, labor and technological resources (Svahn et al., 2017). However, some scholars have also pointed out that the rapid development of digital technology may bring about the problem of "digital divide", exacerbating the imbalance in the distribution of resources and further affecting economic fairness (Yin et al., 2021) Secondly, it is the effect of improving production efficiency. Improving production efficiency is one of the important economic effects brought by digital technology innovation. Digital technology promotes production process intelligence and automation, enabling enterprises to complete more complex production tasks in a shorter period of time (Liu et al., 2023). Studies have shown that the digital transformation of enterprises not only improves production efficiency, but also enhances the competitiveness of enterprises in the global market (Huang et al., 2023). However, at the same time, the spread of digital technology does not always bring linear growth in productivity, and some studies have found that there is still a "Solow Paradox" in the digital era, i.e., technological advances have not been fully converted into real productivity growth (Cheng et al., 2021). This means that further mechanism design and policy guidance are still needed to fully unleash the potential of digital technology. Third, the industrial upgrading effect. Digital technology innovation is regarded as an important driving force to promote the optimization and upgrading of industrial structure. Studies have found that digital technology can break the geographical and time constraints of traditional industries, promote the free flow of resource elements, and promote the extension of the industrial chain and the climbing of the value chain (Wang, 2024). In addition, the deep integration of the digital economy with the real economy, especially in the fields of intelligent manufacturing, digital finance and e-commerce, has made the industrial structure more rational and economic growth more sustainable (Hong & Ren, 2023). However, existing research has mainly focused on the supply side, with less attention paid to how demand-side factors affect the development of the industrial system through industrial structure transformation.

(2) Research on factors influencing the green transformation and upgrading of the manufacturing industry

By combing the existing literature, the factors affecting the green transformation and upgrading of the manufacturing industry are mainly environmental regulation, green taxation, resource endowment, financial agglomeration, green technological innovation and so on. First, environmental regulation. Based on the perspective of environmental efficiency differences between different industries in the manufacturing industry, the institutional soft constraints implemented by local governments have a differentiated impact on the green development of the manufacturing industry, and these institutional constraints impede the transformation of manufacturing industries with a light and medium degree of pollution to a green production mode, but to a certain extent promote the process of environmental protection and transformation of high-pollution industries (Han et al., 2019). Different strengths of environmental regulation can also stimulate different effects, with low-intensity environmental regulation bringing about the "crowding-out effect" and high-intensity environmental regulation bringing about the "innovation compensation effect", leading to differences in the impacts on the green transformation of the manufacturing industry (Sun et al. 2021). There is a significant non-linear relationship between environmental regulation and the green development of the manufacturing industry. That is, when the degree of environmental regulation is low, its promotion effect on green transformation is relatively limited, but with the continuous enhancement of regulatory efforts, this positive effect shows a clear increasing trend (Lei et al., 2020). Second, green taxation. Improving the greening of taxation is an important way to realize the green transformation and upgrading of the manufacturing industry (Gao & Gao, 2017), on the basis of which, green taxation is divided into three dimensions of narrow, medium and broad to analyze in depth, and it is found that the effect of narrow green taxation has not yet been reflected, but the broad or medium green taxation has a significant role in the promotion of green transformation of the manufacturing industry (He et al., 2020). Third, resource endowment. Based on the assessment framework of regional resource endowment, Zhang et al. (2019) explored in-depth the intrinsic influence mechanism of resource elements in the green transformation of manufacturing industry and its spatial spillover effect. Fourth, financial agglomeration. Financial resource agglomeration on the green development of the manufacturing industry presents a nonlinear effect that promotes first and then inhibits later, and its mechanism of action is mainly embodied in the two dimensions of enhancing technological efficiency and promoting technological progress, which in turn affects the dynamic evolution of the green total factor productivity of the manufacturing industry (Guo, 2021). Fifth, green technology innovation. The level of technological research and development is an important factor in promoting the green transformation and upgrading of the manufacturing industry (Li, 2021), and at the same time, green technological innovation is also a key driving force in promoting the green transformation and upgrading of the manufacturing industry (Yuan & Chen, 2019). Among them, green technology innovation represented by cleaner production technology can not only enhance the competitive advantage of enterprises, but also accelerate the transformation and upgrading of enterprises, thus promoting the development of green economy (Eiadat et al., 2008).

2.1.3 Path Study on Digital Technology For Green Transformation and Upgrading of Manufacturing Industry

There is a relative paucity of existing literature examining how green technology innovation affects the green transformation of the manufacturing industry, mainly from the following aspects:

First, digital technological innovation can significantly enhance the green transformation and upgrading of the manufacturing industry by improving resource utilization efficiency and reducing pollutant emissions. Dong et al. (2023) measure the level of digital technological innovation in 30 provinces in China from 2003 to 2019 by using patent search, and the results show that digital technological innovation can not only directly reduce the intensity of carbon emissions, but also indirectly reduce the intensity of carbon emissions through the structural effect and efficiency effect. Li (2023) selected China's industrial input-output panel data from 2011-2021 and found that digital technological innovation can significantly drive industrial carbon emission efficiency, and the empowering effect of digital technological innovation capability on industrial carbon emission efficiency is more obvious in manufacturing industries, western regions and more economically developed regions. Bai Wanting et al. (2024) proposed to optimize the whole life cycle carbon emission management by realizing production data circulation through intelligent cloud platform. Li et al. (2025) found that the digital transformation of enterprises is based on information sharing and knowledge integration, and optimizes the production process and reduces energy consumption and emissions through technological innovations such as artificial intelligence and the Internet of Things. Second, digital technology innovation can influence the green transformation and upgrading of the manufacturing industry by optimizing industrial structure and industrial synergy. Digital technological innovation also promotes the green transformation of the manufacturing industry through industrial structure reconfiguration (Yu, 2023). On the one hand, industrial upgrading enhances the overall efficiency of economic operation by improving the efficacy of resource allocation among industries, and promotes the evolution of the economic development model in the direction of intensification. At the same time, industrial upgrading is conducive to realizing energy saving and efficiency enhancement, which in turn effectively promotes carbon emission reduction and environmental pollution control, and significantly improves green total factor productivity (Guo & Ren, 2023). On the other hand, industrial upgrading can abandon backward production capacity, reduce the proportion of high-energy-consumption, high-pollution and high-emission industries in the economic structure, and accelerate the development of strategic emerging industries, advanced manufacturing industries, and modern service industries (Liu & Wang, 2022), thus promoting the green transformation and upgrading of the manufacturing industry. In addition, the impact of digital technology innovation on the green transformation of the manufacturing industry is also affected by factors such as environmental regulation. Zhang (2020) suggests that when the strength of environmental regulation is moderate, digital technology can form a "complementary effect" through green technological innovation and compliance management, which will promote the transformation into a rapid development period, but too strong regulation may lead to technological lock-in. Research in the Yangtze River Economic Belt shows that digital transformation improves the efficiency of green development in the manufacturing industry by facilitating green technological innovation (Wu et al., 2022). However, regional digitization levels need to cross a threshold before green technology innovation can significantly improve green total factor productivity, and its marginal effect is characterized by "incremental" (Xiao et al., 2023).

2.1.4 Literature Review

On the basis of combing the existing literature, it can be found that academics have carried out more comprehensive research around digital technology innovation and green transformation of manufacturing industry, and have made significant progress in measuring digital technology innovation and green transformation of manufacturing industry. And on this basis, the influence factors and enhancement paths of digital technology innovation and manufacturing green transformation and upgrading have been argued from both theoretical and empirical dimensions. However, there are still the following shortcomings: first, most of the literature is based on the provincial or economic circle level to analyze the role of digital technology innovation on the transformation and upgrading of the manufacturing industry, and it is difficult to put forward constructive opinions at the micro level as a whole, which is relatively limited. Although this kind of macro-level research can reveal the overall trend and general laws, it is unable to deeply understand the differences and characteristics between micro subjects of different sizes, ownerships, industries and so on. Second, the existing literature mostly studies the relationship between technological innovation on economic transformation or manufacturing transformation, and relatively few studies on the green transformation and upgrading of the manufacturing industry. Existing literature on the role of digital technological innovation to influence the green transformation and upgrading of the manufacturing industry mechanism and path of research is relatively insufficient, mostly stay in the surface description and simple correlation analysis. Under the current background of global green development, the green transformation of the manufacturing industry has become an important trend, and more research is needed to focus on this field and explore in depth the unique role and influence mechanism of digital technology innovation in it. Thirdly, the measurement of relevant indicators is not yet objective, and there are differences in the selection of indicators, which can easily lead to subjective errors and make it difficult to fully explain the meaning of indicators. The data used in some studies may have the problem of timeliness and cannot reflect the latest development. At the same time, the sample size of some studies is small or there are biases in the selection of samples, which affects the representativeness and reliability of the conclusions of the studies.

3. Research Hypotheses

3.1.1 Impact of Digital Technology Innovation on Green Transformation and Upgrading of Manufacturing Industry

As the digital economy continues to develop, it has become an important engine for high-quality economic development. Digital technological innovation introduces data elements into the allocation of production factors, helping the manufacturing industry to transform and upgrade in a green way. In the context of global sustainable development, the manufacturing industry is faced with the dual challenge of both improving production efficiency and reducing environmental impact. Digital technological innovation can promote the green transformation and upgrading of the manufacturing industry in terms of reducing transaction costs, upgrading human capital and alleviating information asymmetry.

First, reduce transaction costs. With the deep application of digital technology in the field of manufacturing, the role of digital technological innovation in reducing transaction costs has become increasingly prominent. With the rapid evolution of the new generation of information technology, enterprises are able to quickly locate and integrate various types of information with the help of digital platforms, effectively reducing the cost of information acquisition (Li et al., 2024). The application of Internet-based technologies, such as smart contracts, dramatically cuts down the time and material costs in the traditional contracting process. Innovative technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) have improved supply chain management, reduced transportation costs and increased transportation efficiency. In addition, digital technology can improve the market price mechanism, make the allocation of carbon emission allowances more reasonable and fair, alleviate the problem of information asymmetry, reduce transaction costs, improve market efficiency, further promote the improvement of energy utilization and allocation efficiency (Huang et al., 2023), and effectively promote the green transformation and upgrading of the manufacturing industry.

Second, upgrading human capital. Digital technology innovation can promote the upgrading of human capital structure, and the enhancement of human capital can further promote the green transformation and upgrading of manufacturing industry. Digital technology innovation can be embedded in intelligent production equipment and digital management platform, reshape the structure of labor force skills demand, prompting enterprises to increase investment in the cultivation of composite talents with digital skills and green technology, enhance the digital literacy of employees, and enhance the accumulation of knowledge of environmental management and the ability of innovation and collaboration. Human capital mastering advanced digital technology can, through its unique innovative power, bring about innovation in means of production and skills, thus promoting the green transformation of the manufacturing industry. In addition, the agglomeration and spillover effect of human capital further promotes the innovation and development of green technology, accelerating the green transformation and upgrading process of the manufacturing industry. Human capital with rich knowledge and skills not only contributes to technological innovation within enterprises, but also inspires employees to propose new green technology solutions or improve existing processes, further accelerating the process of green transformation of the manufacturing industry.

Third, mitigating information asymmetry. Information asymmetry is an important factor constraining the green transformation and upgrading of the manufacturing industry. In the traditional manufacturing industry, due to the lack of an effective information sharing platform, there are often information barriers between upstream and downstream enterprises, leading to resource waste and environmental problems. Digital technology innovation effectively alleviates this problem by building a transparent information platform. First, supply chain transparency. The application of blockchain technology makes the data of each link in the supply chain open and transparent, ensuring that all participants can access accurate information in real time. This not only improves the overall efficiency of the supply chain, but also enhances the social responsibility of enterprises. A transparent supply chain helps to reduce unnecessary waste of resources and improve overall resource utilization efficiency. Second, market information sharing. Big data analysis and cloud computing technology help enterprises better understand changes in market demand, adjust production plans in a timely manner, and avoid overproduction and resource waste. Transparency of market information enables enterprises to respond faster to market changes, reduce the inventory pressure of slow-selling products, and then reduce resource consumption. Finally, environmental regulation transparency. Digital technology can also be applied to the field of environmental regulation, through real-time monitoring and data analysis, to ensure that enterprises comply with environmental regulations. A transparent environmental regulatory mechanism not only improves corporate compliance, but also enhances social trust in corporate environmental behavior. Based on this, this paper proposes the following hypothesis:

Hypothesis 1: Digital technology innovation contributes to the green transformation and upgrading of manufacturing industries

4. Research Design and Empirical Modeling

4.1 Selection of Variables

4.1.1 Explained Variables

(1) The explanatory variable is green transformation and upgrading of manufacturing industry ($GTFP$). The core connotation of green total factor productivity in the manufacturing industry is to incorporate resource and environmental constraints on the basis of traditional total factor productivity, reflecting the incremental productivity brought about by technological progress and capability improvement after excluding the contribution of labor and capital factors. Under the guidance of the new development concept, the enhancement of green total factor productivity in the manufacturing industry needs to be driven by technological innovation, and at the same time, it is necessary to incorporate green development dimensions such as energy efficiency and ecological environmental protection into the evaluation system, so as to realize the synergistic enhancement of economic and ecological benefits. With the in-depth promotion of the construction of ecological civilization, the green total factor productivity of the manufacturing industry has become a key indicator for assessing the level of sustainable development of the manufacturing industry, and the results of its measurement can more comprehensively reflect the quality and benefits of the development of the manufacturing industry. Therefore, this paper believes that the green total factor productivity of the manufacturing industry under the new development concept can better show the development of the manufacturing

industry, and also adopts this indicator to measure the effect of green transformation of the manufacturing industry.

4.1.2 Explanatory Variables

The explanatory variable is digital technology innovation (Tec). In this paper, the number of digital patent applications is chosen to measure the level of digital technology innovation. Digital technology patents are the visual embodiment of the enterprise's technological innovation achievements, which can be directly put into production and application, and can effectively demonstrate the actual achievements of the enterprise in the field of digital technological innovation, which is one of the key indicators to measure the level of enterprise technological innovation. Drawing on the experience of scholars such as Huang et al. (2023) in measuring digital technological innovation, the number of digital patent applications is obtained by keyword text analysis of patent application reports and other documents based on relevant official documents and reports.

4.1.3 Control Variables

This paper examines the micro level, and enterprise characteristics are also important variables affecting the green transformation and upgrading of the manufacturing industry. In order to avoid the problem of biased regression results caused by the omission of other important explanatory variables, this paper adds control variables such as gearing ratio, total asset turnover ratio, independent director ratio, return on net assets, fixed asset ratio, total asset growth rate and market net worth.

4.1.4 Mechanism Variables

(1) Transaction costs ($tran$). Transaction costs include all costs incurred throughout the transaction process, including the cost of searching for information, the cost of reaching and signing a contract, the cost of supervising the execution of the contract, and the cost of seeking compensation after a breach of contract. In view of the controversy in academia over the measurement of transaction costs, and considering the availability of data and the impact of firm size on transaction costs, this paper adopts the measure proposed by Li and Zhang (2023), i.e., the ratio of the sum of the selling, administrative and financial expenses to the total assets to measure the transaction costs of a firm.

(2) Human capital (HC). The improvement of human capital structure can enhance the production efficiency, and at the same time provide the necessary skilled labor resources for the digital technology innovation activities of enterprises, so as to promote the green transformation and upgrading of the manufacturing industry. In order to effectively reflect the quality and structure of the enterprise's human capital, this paper refers to the research of Shen et al. (2024), which can use the percentage of employees with bachelor's degree and above as an indicator to measure the academic structure of the enterprise's employees.

(3) Information asymmetry (ASY). Information asymmetry is one of the important factors leading to total factor productivity differences among enterprises. Advanced digital technologies such as big data and artificial intelligence can centralize the processing of massive data and mine more comprehensive user information, thus reducing information asymmetry (Lin et al., 2013; Huang et al., 2018). Referring

to Yu et al. (2012) and Song et al. (2021), this paper selects the liquidity ratio, the illiquidity ratio, and the inversion indicator for principal component analysis to construct a comprehensive indicator of information asymmetry (ASY), and the larger value of this indicator indicates the more serious information asymmetry.

Table 4-2 Variable Definitions and Descriptions

Variable category	variable representation	variable name	Variable Definition
explanatory variable	*GTFP*	Green transformation and upgrading of the manufacturing sector	Green total factor productivity
Core explanatory variables	*Tec*	Digital technology innovation	Digital Economy Patent Filings
control variable	*Lev*	gearing	Total liabilities at year-end/total assets at year-end
	ATO	Total asset turnover	Operating income/average total assets
	Indep	Ratio of independent directors	Independent directors divided by number of directors
	ROE	return on net assets	Net profit/average balance of owners' equity
	Fixed	Fixed assets as a percentage	Net fixed assets/total assets
	AssetGrowth	Total asset growth rate	Total assets for the current year/total assets for the previous year - 1
	PB	market capitalization ratio	Price per share/net assets per share
transaction cost	*tran*	transaction cost	Sum of selling, administrative and financial expenses/total assets
human capital	*HC*	Human capital structure	Percentage of employees with bachelor's degree or above
information asymmetry	*ASY*	Composite indicator of information asymmetry	Construction of a composite indicator of information asymmetry

4.2 Modeling

4.2.1 Benchmark Regression Model

In order to carry out the empirical test of the direct impact of digital technology innovation and green transformation and upgrading of the manufacturing industry, with reference to the experience of modeling by scholars such as Shuai-Na Li et al. (2024), this paper first constructs the following panel benchmark model:

$$GTFP_{it} = \alpha_0 + \alpha_1 \ln Tec + \alpha_j \sum X_{jit} + \mu_{it} \tag{4.5}$$

Among them, i represents the enterprises, t represents the year, $\ln\mathrm{Tec}_{it}$ represents the level of digital technological innovation, which is the core explanatory variable of this paper; GTFP_{it} represents the green total factor productivity of each listed manufacturing enterprise, which is the explanatory variable of the model. The regression coefficient α_1 is the main object of observation in this paper, according to the sign of α_1 and the significance level can analyze the direction and degree of the impact of digital technological innovation on the green transformation and upgrading of the manufacturing industry, so as to reflect the degree of the impact of digital technological innovation on the green transformation and upgrading of the manufacturing industry. X_{it} A series of control variables are included, while individuals and years are fixed, and μ_{it} is a random perturbation term.

5. Empirical Results and Analysis

5.1 Descriptive Statistical Analysis

Table 5-1 demonstrates the descriptive statistics of all the research variables in this paper, which fully demonstrates the basic distribution of the sample data, with the specific indicators shown in the Table.

The explanatory variable is green transformation and upgrading of the manufacturing industry, with a mean of 0.911, a standard deviation of 0.441, a maximum value of 2.932, and a minimum value of 0.031, indicating that the sample enterprises have significant individual differences, and that high-energy-consuming enterprises are less efficient, probably due to enterprise heterogeneity. The explanatory variable is digital technological innovation (Tec), with a mean value of 1.974525, a maximum value as high as 8.867004, and a minimum value of 0, with a standard deviation of 1.776643, reflecting an extreme imbalance of technological investment among enterprises. Some enterprises may invest in technology on a large scale due to policy support or industry demand, while traditional enterprises lag behind in technology updating. The mechanism variables are transaction cost, human capital and information asymmetry. The mean value of transaction costs is 0.095 and the standard deviation is 0.0685576, indicating that there are some differences in transaction costs among different enterprises, but the degree of difference is relatively small. The standard deviation of human capital is 0.161258, indicating that human capital varies greatly among different samples, and there may be some enterprises with higher levels of human capital and some with lower levels. The standard deviation of information asymmetry is 0.5643641, indicating that information asymmetry varies greatly across samples, with some enterprises facing serious information asymmetry problems, while some enterprises may have smoother information flow channels.

Table 5-1 Results of Descriptive Statistics

variable name	variable symbol	sample size	average value	(statistics) standard deviation	minimum value	maximum values
Green transformation and upgrading of the manufacturing sector	*GTFP*	11,430	0.911	0.441	0.0311	2.932
Digital technology innovation	*Tec*	11,430	1.974525	1.776643	0	8.867004
gearing	*Lev*	11,430	0.409	0.186	0.00797	1.150
Total asset turnover	*ATO*	11,430	0.657	0.418	0.00345	7.609
Ratio of independent directors	Indep	11,430	0.375	0.0561	0	0.800
return on net assets	*ROE*	11,430	0.0489	0.556	-20.99	20.75
Fixed assets as a percentage	*Fixed*	11,430	0.235	0.135	0.000206	0.808
Total asset growth rate	*AssetGrowth*	11,430	0.145	0.529	-0.659	24.44
market capitalization ratio	*PB*	11,430	3.050	3.851	0	5.413981
transaction cost	*trab*	11,430	0.0951288	0.0685576	0	0.4044556
human capital	*HC*	11,430	0.2599313	0.161258	0.001935	0.934793
information	*ASY*	11,430	-0.3324491	0.5643641	-7.223508	2.826715

asymmetry

5.2 Multicollinearity Test

In this paper, all indicators in the study were tested for multicollinearity to ensure the validity of the test estimates in the later section, and the test results are shown in Table 5-2. ROE The VIF of the variables is the largest, but it is only 1.36, and the VIF values of all the variables are all much less than 10. this indicates that the independence between the variables is strong, and there is no problem of multicollinearity.

Table 5-2 Multiple Covariance Tests

Variable	VIF	1/VIF
ROE	1.36	0.733406
PB	1.32	0.755361
Lev	1.17	0.853007
lnTec	1.11	0.89953
Fixed	1.09	0.918889
ATO	1.06	0.941593
AssetGrowth	1.01	0.985385
Indep	1	0.997324

5.3 Benchmark Regression Results

The paper next examines the impact of digital technology innovation on green transformation and upgrading in the manufacturing sector using panel fixed and random effects. The first two columns of Table 5-3 exhibit random effects, where the estimation results in column (1) do not introduce control variables and the estimated coefficients of the digital technology innovation variables are significantly positive. While column (2) introduces control variables such as gearing ratio, total asset turnover ratio and percentage of independent directors, the estimated coefficients of digital technology innovation variables are significantly positive. The last two columns are fixed effects, of which those in column (3) are the estimation results without considering the inclusion of control variables, and the estimated coefficient of the digital technology innovation variable is significantly positive. While column (4) includes control variables such as gearing ratio, total asset turnover ratio and percentage of independent directors, the estimated coefficient of the digital technology innovation variable is significantly positive.

The results of empirical analysis show that the regression coefficient of digital technological innovation is significantly positive, and the result is not affected by the selection of control variables and model setting, which confirms that digital technological innovation has a significant role in promoting the green transformation and upgrading of the manufacturing industry. From column (4) in Table 5-3, the estimated coefficient of digital technological innovation is 0.028, indicating that for every 1 unit increase in the level of digital technological innovation, the level of green transformation of the manufacturing industry rises by 0.028, which indicates that digital technological innovation can significantly promote the green transformation and upgrading of the manufacturing industry.

Table 5-3 Benchmark Regression Results

variant	(2) *GTFP*	(1) *GTFP*	(3) *GTFP*	(4) *GTFP*
lnTec	0.069 ***	0.057 ***	0.029 ***	0.028 ***
	(0.005)	(0.005)	(0.007)	(0.006)
Lev		0.011		-0.236 ***
		(0.047)		(0.051)
ATO		0.668 ***		0.770 ***
		(0.021)		(0.023)
Indep		0.206*		-0.004
		(0.125)		(0.127)
ROE		0.010		0.016*
		(0.010)		(0.009)
Fixed		-1.718 ***		-2.176 ***
		(0.068)		(0.074)
AssetGrowth		-0.001		0.009
		(0.009)		(0.009)
PB		0.000		0.004 ***
		(0.002)		(0.002)
Constant	0.864 ***	0.769 ***	2.257 ***	3.103 ***
	(0.021)	(0.058)	(0.154)	(0.156)
N	11,430	11,430	11,430	11,430
timing	NO	NO	YES	YES
individually	NO	NO	YES	YES

Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, below.

5.4 Endogeneity Tests and Robustness Tests

5.4.1 Instrumental Variables Approach

Digital technological innovation contributes to the enhancement of green transformation and upgrading of the manufacturing industry, and similarly affects the direction and level of digital technological innovation when the manufacturing industry is green and sustainable. Therefore, considering the possible endogeneity problem due to bidirectional causality between the explained variable manufacturing green transformation and upgrading and the explanatory variable digital technological innovation explored in this paper. Drawing on the ideas of Yang et al. (2019), this paper takes into account the lagged nature of the impact of the application of digital technological innovation, and selects the lagged one period of the level of digital technological innovation as an instrumental variable to be included in the regression equation, in order to solve the possible endogeneity problem. The estimation results of the two-stage least squares method for instrumental variables are shown in Tables 4-8, and the F-values of the Cragg-Donald Wald F statistic for the weak instrumental variable test are all greater than the critical value at the 10% level of the Stock-Yogo test, which indicates that the selected instrumental variables are reasonable. Second, column (1) of Table 5-4 shows the results of the first-stage estimation, where the regression coefficients for digital technological innovation lagged one period are significantly positive, indicating that there is a strong correlation between the selected instrumental variables and digital technological innovation. Column (2) shows the regression results of the second stage, digital technology innovation is significant at the 1% level, with a regression coefficient of 0.071, indicating that digital technology innovation has a positive facilitating effect on the green transformation and upgrading of the manufacturing industry, which is consistent with the previous baseline regression results, and Hypothesis 1 is supported again.

Table 5-4 Regression Results for Two-Stage Least Squares

	(1)	(2)
	First stage	Second stage
variant	*lnTec*	*GTFP*
lnTec		0.071 ***
		(14.116)
lnTec _ lag	0.908 ***	
	(209.731)	
Lev	0.248 ***	0.325 ***
	(5.924)	(7.271)
ATO	-0.052	0.272**
	(-0.407)	(2.015)
Indep	0.009	0.307 ***
	(0.488)	(16.338)
ROE	0.013	0.047 ***
	(0.938)	(3.267)
Fixed	-0.298 ***	0.342 ***

	(-5.368)	(5.783)
AssetGrowth	0.110 ***	0.050 ***
	(8.372)	(3.607)
PB	-0.002	0.003
	(-0.793)	(1.484)
Cragg-Donald Wald F statistic		8461.686 ***
Constant	0.246 ***	0.321***
	(4.596)	(5.661)
N	10,475	10,475
r^2		0.066

5.4.2 Replacement of Estimation Methods

The previous paper adopted the random effects model and fixed effects model to test the direct impact of digital technology innovation on green transformation and upgrading of the manufacturing industry, but there is a certain bias in this estimation. In order to alleviate the possible problems of intra-group autocorrelation, inter-group contemporaneous correlation and inter-group heteroskedasticity in the benchmark regression, the sample is first reduced by 1%, and the generalized least squares (xtgls) two-way fixed model is used to estimate the sample again, and the results, as shown in Column (1) of Table 5-5, indicate that the regression coefficients of digital technological innovation are significantly positive. After changing the estimation method, the findings remain the same, indicating that the baseline regression results are robust.

Table 5-5 Regression Results after Replacing Estimates

	(1)
variant	*GTFP*
lnTec	0.0723***
	(0.00605)
Lev	0.306 ***
	(0.0609)
ATO	0.331 ***
	(0.0383)
Indep	0.308**
	(0.143)
ROE	0.115 **
	(0.0585)

Fixed	0.565 ***
	(0.0851)
AssetGrowth	0.0505**
	(0.0235)
PB	0.00289
	(0.00261)
Constant	0.238 ***
	(0.0609)
N	8,360
r^2	0.080

5.4.3 Subsample Regression

Considering that highly polluting enterprises will produce certain bias on the results of this paper, in order to avoid the impact of highly polluting enterprises on the green transformation and upgrading of manufacturing industry, all the sample data of listed highly polluting enterprises are excluded and re-tested, and the results are shown in Tables 5-6. From the results, it can be seen that there is a significant positive relationship between digital technology innovation on the green transformation and upgrading of manufacturing industry, which further indicates that the empirical results of this paper are relatively robust.

Table 5-6 Regression Results Excluding Highly Polluting Firms

	(1)
variant	*GTFP*
lnTec	0.017**
	-0.008
Lev	0.101
	-0.07
ATO	0.948 ***
	-0.039
Indep	-0.186
	-0.158
ROE	0.184 ***
	-0.04
Fixed	-2.357 ***
	-0.11

AssetGrowth	0.002
	-0.011
PB	0
	-0.003
Constant	0.061
	-0.159
N	6068
timing	YES
individually	YES

5.4.4 Replacement of Explanatory Variables

In order to test the accuracy and robustness of the benchmark regression results, this paper replaces the measure of green transformation and upgrading of the manufacturing industry, and further explores whether the measurement method of the explanatory variables has an impact on the regression results. Considering the summarizing and guiding characteristics of annual report information, green transformation is a more important strategic information of listed enterprises, which will be disclosed in public policy documents or annual reports. At the same time, the format and wording of annual reports of listed companies are more strict, which helps to improve the efficiency of keyword matching. Therefore, we refer to LOUGHRAN and MCDONALD (2011) to measure the transformation and upgrading of manufacturing firms through the disclosure of information in annual reports. Referring to the experience of scholars such as Zhou et al. (2022), 113 keywords related to green transformation are selected based on relevant policy documents, and the frequency of keywords appearing in the annual reports of listed manufacturing enterprises is counted to form the greening transformation word frequency number, which is logarithmically calculated by adding 1 to measure the greening transformation level of the manufacturing enterprises (*gre*). Table 5-7 shows the regression results with the explanatory variables replaced and fixed time effects and individual effects. As can be seen from column (1) of Table 5-7, the regression coefficient of digital technological innovation is still significantly positive, which is consistent with the benchmark regression results, indicating the robustness of the benchmark regression results.

Table 5-7 Regression Results for Replacing Explained Variables

	(1)
variant	*gre*
lnTec	0.025^{***}
	(0.007)
Lev	0.047

	(0.052)
ATO	-0.011
	(0.024)
Indep	0.026
	(0.129)
ROE	0.011
	(0.010)
Fixed	0.069
	(0.075)
AssetGrowth	0.014
	(0.009)
PB	-0.001
	(0.002)
Constant	1.597 ***
	(0.159)
N	11,422
timing	YES
individually	YES

5.5 Heterogeneity Analysis

5.5.1 Analysis of Regional Heterogeneity

There are also obvious differences in the level of manufacturing development between regions in China due to resource endowment, industrial policy, marketization level and other factors, so the impact of digital technology innovation on the green transformation and upgrading of manufacturing industry should be obviously different in different regions. Therefore, this paper refers to the treatment of Shen et al. (2021) scholars, according to the region they are located in the sample of each enterprise is categorized into three categories: east, central and west, respectively, to examine the impact of the level of digital technological innovation on the green transformation and upgrading of manufacturing industry in the three types of regions.

Table 5-8 demonstrates the results of the impact of digital technology innovation on the green transformation and upgrading of manufacturing industry in different regions. From columns 1 to 3 of Table 5-8, it can be seen that the regression coefficient of digital technological innovation level in the eastern region is 0.015, and it is significant at the 5% level; the regression coefficient of digital technological innovation level in the western region is 0.118, and it is significant at the 1% level; the regression coefficient of digital technological innovation level in the central region is 0.020, and it is significant at the 5% level. Overall, digital technology innovation in the East, Central and West regions can promote the green transformation and upgrading of the manufacturing industry. On the one hand, digital technology can realize intelligent monitoring and real-time optimization of the production process through the industrial Internet, big data analysis and other technical means, reduce energy consumption and pollutant emissions, thus promoting the green transformation and upgrading of the manufacturing industry. On the other hand, digital technology-driven innovation diffusion effect can break through geographical restrictions, promote technology overflow and knowledge sharing, and gradually form a regional specialization of green manufacturing mode, providing impetus for the green transformation and upgrading of manufacturing industry in East, Central and West China.

Table 5-8 Regression Results for Regional Heterogeneity

	(1)	(1)	(1)
	Eastern Enterprises	Western Enterprises	Central Enterprises
variant	*GTFP*	*GTFP*	*GTFP*
lnTec	0.015**	0.118 ***	0.020**
	(0.008)	(0.020)	(0.010)
Lev	-0.083	-0.350**	0.059
	(0.062)	(0.150)	(0.097)
ATO	0.717 ***	1.176 ***	0.739 ***
	(0.028)	(0.068)	(0.050)
Indep	-0.029	-0.053	0.152
	(0.156)	(0.340)	(0.228)
ROE	0.076 ***	-0.007	0.406 ***
	(0.020)	(0.016)	(0.074)
Fixed	-2.102 ***	-2.732 ***	-1.956 ***
	(0.092)	(0.182)	(0.147)
AssetGrowth	-0.014	0.100 ***	0.006
	(0.012)	(0.023)	(0.013)
PB	0.000	-0.003	0.009**
	(0.003)	(0.006)	(0.004)
Constant	3.092 ***	0.507**	0.851 ***
	(0.163)	(0.225)	(0.314)
N	7,639	1,591	1,614
timing	YES	YES	YES
individually	YES	YES	YES

5.5.2 Analysis of Heterogeneity in Factor Intensity

Factor intensity is classified according to the main production factors that enterprises rely on in the production process, and is usually divided into technology-intensive, capital-intensive and labor-intensive. Enterprises with different factor intensities have significant differences in production factor dependence, innovation demand and ability, and policy response, etc. These differences will affect the effect of digital technology innovation on the green transformation and upgrading of the manufacturing industry. To study the impact of digital technological innovation on the structural upgrading of the manufacturing industry, it is necessary to classify manufacturing industry segments into three major categories of labor-, capital- and technology-intensive industries based on the differences in their factor intensities. Drawing on the classification method of scholars such as Yang Ligao (2014), the manufacturing industry is divided into three categories of labor, capital and technology intensive.

Based on the above classification of the manufacturing industry, this paper carries out an empirical analysis of the impact between digital technological innovation and green transformation and upgrading of the manufacturing industry on the basis of the technology-intensive, capital-intensive and labor-intensive, respectively, and the results of the specific analysis are shown in Table 5-9.

In technology-intensive, the regression coefficient of digital technology innovation is 0.012, but not significant, indicating that in technology-intensive enterprises, the impact of digital technology innovation on green transformation and upgrading is weak. On the one hand, the technology-intensive industry itself has high technical complexity and path dependence, and its green transformation often needs to break through the rigid constraints of the existing technological system, while the application of digital technology may not yet have formed an innovation ecology that is deeply adapted to the characteristics of the industry. On the other hand, institutional barriers may weaken the actual effectiveness of digital technology innovation. The intellectual property protection mechanism of technology-intensive industries is still imperfect, and manufacturing enterprises may inhibit the open sharing of digital platforms and hinder the cross-domain integration of data resources in order to avoid the spillover of core technologies, leading to insufficient synergistic effects of digital technology and thus restricting the green transformation of the manufacturing industry. In the capital-intensive group, the regression coefficient of 0.071 for digital technology innovation is significant at the 1% level, indicating that digital technology innovation has a significant positive effect on green transformation and upgrading in capital-intensive enterprises. It may be because such enterprises have strong capital and can effectively support digital technology innovation and green project investment. In the labor-intensive group, the regression coefficient of 0.029 for digital technological innovation is significant at the 5% level, indicating that digital technological innovation also has a certain positive effect on green transformation and upgrading in labor-intensive enterprises. It may be because such enterprises improve productivity and resource utilization through digital technology innovation to promote green transformation in the manufacturing industry.

Table 5-9 Heterogeneity Regression Results Based on Factor Intensity

	(1) technology-intensive	(1) capital-intensive	(1) labor-intensive
variant	*GTFP*	*GTFP*	*GTFP*
lnTec	0.012	0.071 ***	0.029**
	(0.008)	(0.016)	(0.012)
Lev	0.093	-0.375**	-0.170
	(0.077)	(0.146)	(0.109)
ATO	1.038 ***	1.036 ***	0.558 ***
	(0.044)	(0.072)	(0.036)
Indep	-0.154	0.299	0.048
	(0.177)	(0.347)	(0.227)
ROE	0.173 ***	0.070**	0.480 ***
	(0.043)	(0.033)	(0.075)
Fixed	-2.555***	-2.190 ***	-1.147 ***
	(0.122)	(0.181)	(0.162)
AssetGrowth	-0.018	0.038**	0.023*
	(0.015)	(0.016)	(0.012)
PB	0.001	0.005*	-0.005
	(0.004)	(0.003)	(0.005)
Constant	-0.009	2.537 ***	1.131 ***
	(0.168)	(0.242)	(0.153)
N	5,362	1,547	1,451
timing	YES	YES	YES
individually	YES	YES	YES

5.5.3 Heterogeneity Analysis of Government Subsidies

Government subsidies are crucial to digital technology innovation, and the size of subsidies directly affects R&D investment and competitive dynamics in manufacturing industries, and different subsidy sizes may influence through different channels. For example, high-subsidized firms prefer long-term basic research, while low-subsidized firms focus on short-term experimental development (Guo & Cheng, 2016). High-subsidized firms may have broken through financing bottlenecks, and the marginal utility of subsidies is diminishing; low-subsidized firms are still subject to financial constraints, and subsidies have a stronger leveraging effect on their R&D or innovation activities (Guo & Cheng, 2016). Therefore, in this paper, the sample is divided into three groups of high, medium, and low according to the ratio of government subsidies to operating revenues or total assets for heterogeneity analysis respectively.

Table 5-10 shows the results of the impact of digital technology innovation on green transformation and upgrading of the manufacturing industry at different levels of government subsidies. In the high subsidy group, the regression coefficient of digital technological innovation is 0.048 and is significant at the 1% level; in the medium subsidy group, the regression coefficient coefficient of digital technological innovation is not significant; in the low subsidy group, the regression coefficient coefficient of digital technological innovation is 0.028 and is significant at the 5% level. This shows that digital technology innovation has a positive impact on the green transformation and upgrading of the manufacturing industry in the high and low subsidy groups, but it is not significant in the medium subsidy group. This may be due to the fact that highly subsidized enterprises have sufficient resources to support innovation, making it easier to obtain external green certifications and amplifying the environmental benefits of technological innovation. Low-subsidy enterprises may be more inclined to make up for the funding gap by optimizing internal resource allocation and R&D investment intensity, and improve the market transformation capacity of digital technology innovation, so as to optimize production processes and reduce energy intensity, thereby promoting the green transformation of enterprises. However, medium-subsidized enterprises may be in an intermediate state, and the allocation of resources is not effective enough, which may lead to strategic innovation behaviors (such as emphasizing the quantity of patents over quality), resulting in a decline in the efficiency of technology transformation.

Table 5-10 Heterogeneity Regression Results Based on the Extent of Government Subsidies

	(1)	(2)	(3)
	Highly subsidized group	Medium Subsidized Group	Unsubsidized group
variant	*GTFP*	*GTFP*	*GTFP*
lnTec	0.048 ***	0.009	0.028**
	(0.013)	(0.011)	(0.012)
Lev	0.004	0.201*	-0.170
	(0.119)	(0.106)	(0.104)
ATO	0.450	-0.436*	-0.145
	(0.273)	(0.229)	(0.247)
Indep	0.743 ***	1.093 ***	1.233 ***
	(0.039)	(0.063)	(0.085)
ROE	0.140 **	0.266 ***	0.022
	(0.057)	(0.072)	(0.049)
Fixed	-2.579 ***	-2.310 ***	-2.220 ***

	(0.170)	(0.166)	(0.161)
AssetGrowth	0.024**	0.015	-0.025
	(0.012)	(0.034)	(0.022)
PB	0.005	-0.009*	0.003
	(0.004)	(0.005)	(0.005)
Constant	-0.433	3.396 ***	2.668 ***
	(0.465)	(0.232)	(0.214)
N	2,336	3,412	2,612
timing	YES	YES	YES
individually	YES	YES	YES

5.6 Analysis of Impact Mechanisms

5.6.1 Analysis of Mechanisms to Reduce Transaction Costs

Tables 5-11 report the results of the mechanism test of transaction cost in digital technology innovation affecting the green transformation and upgrading of manufacturing industry. Column (1) demonstrates the total effect of transaction costs on green transformation and upgrading of the manufacturing industry, and column (2) demonstrates the results of regression of transaction costs as an explanatory variable on digital technological innovation, the regression coefficient of which is significantly negative at the 1% level, suggesting that digital technological innovation is able to reduce transaction costs. Column (3) demonstrates the estimation results of putting transaction cost into the benchmark regression model, and the regression coefficient of transaction cost is significantly negative at the 1% level, indicating that digital technology innovation can promote the green transformation and upgrading of the manufacturing industry through the channel of action of reducing transaction cost. In order to ensure the reliability of the research results, this paper adopts the Sobel test for the test of the channel of action. The Sobel test Z-value of the effect of reducing transaction costs is 5.536, and the P-value is less than 0.01, and the mechanism effect of reducing transaction costs is established.

The possible reason is that the increasing innovation ability of digital technology helps data resources to be constantly enriched, which can break through the geospatial constraints and optimize the information transfer mechanism, and significantly reduce the transaction costs of each link in the industrial chain (Zhu & Wang, 2017). Therefore, digital technology innovation can reduce transaction costs. At the same time, the integration of digital technological innovation and manufacturing industry can improve the efficiency of factor allocation, reduce the consumption of intermediate goods in the production process, improve the efficiency of capital turnover and shorten the production time, thus promoting the green transformation of the manufacturing industry. In addition, digital technology innovation can optimize supply chain management, can reduce transportation costs, operating costs, improve logistics efficiency, and indirectly promote the green transformation of manufacturing enterprises.

Table 5-11 Results of Mechanism Tests for Reducing Transaction Costs

	(1)	(2)	(3)
variant	*GTFP*	*tran*	*GTFP*
lnTec	0.028 ***	-0.001 ***	0.051 ***
	(0.006)	(0.000)	(0.004)
tran			-0.377 ***
			(0.108)
Lev	-0.236 ***	0.040 ***	0.257 ***
	(0.051)	(0.003)	(0.040)
ATO	-0.004	0.007	0.174
	(0.127)	(0.007)	(0.124)
Indep	0.770 ***	0.041 ***	0.286 ***
	(0.023)	(0.001)	(0.017)
ROE	0.016*	-0.000	0.060 ***
	(0.009)	(0.001)	(0.014)
Fixed	-2.176 ***	0.054 ***	0.328 ***
	(0.074)	(0.004)	(0.054)
AssetGrowth	0.009	-0.006 ***	0.064 ***
	(0.009)	(0.001)	(0.013)
PB	0.004 ***	0.000 ***	0.007 ***
	(0.002)	(0.000)	(0.002)
Constant	1.035 ***	0.039 ***	0.469 ***
	(0.058)	(0.003)	(0.053)
N	11,428	11,428	11,430
R-squared	0.647	0.850	0.080
timing	YES	YES	YES
individually	YES	YES	YES
Sobel test	5.536 ***		

5.6.2 Analysis of Mechanisms to Enhance Human Capital

Table 5-12 reports the results of the mechanism test of human capital in digital technology innovation affecting the green transformation and upgrading of manufacturing industry. The results of column (1) have been shown in the previous section, and column (2) demonstrates the regression results of human capital as an explanatory variable on digital technological innovation, with a regression coefficient of 0.004 and significant at the 1% level, which indicates that there is a significant facilitating effect of digital technological innovation on human capital. Column (3) demonstrates the estimation results of putting human capital into the benchmark regression model, and the regression coefficient of human capital is significant at the 1% level, indicating that the mechanism effect of human capital exists significantly. In order to ensure the reliability of the research results, this paper adopts the Sobel test for the channel of action. The Sobel test Z-value of the mechanism effect of human capital is 11.65, and the P-value is less than 0.01, the mechanism effect of human capital is established.

Digital technological innovation can promote cross-enterprise, cross-field R&D collaboration, so that human capital in the open innovation environment to accumulate green technology knowledge, reducing the cost of knowledge acquisition, accelerating the staff's mastery of technology, and then optimize the skill structure of the manufacturing industry practitioners. Therefore, digital technology innovation can promote human capital upgrading. Human capital upgrading can promote the efficiency of green technology research and development, accelerate the transformation of green patent results, especially in the development of technology application scenarios, high-quality personnel through the skills iteration to promote the technology to the ground (Li, 2023), which in turn promotes the green transformation and upgrading of the manufacturing industry. At the same time, human capital upgrading can also reduce the energy consumption of equipment and facilities, improve energy utilization, and promote the greening of production processes, thus promoting the green transformation and upgrading of the manufacturing industry.

Table 5-12 Results of Mechanism Tests for Enhancing Human Capital

	(1)	(2)	(3)
variant	*GTFP*	*HC*	*GTFP*
lnTec	0.028 ***	0.004 ***	0.024 ***
	(0.006)	(0.001)	(0.006)
HC			0.319 ***
			(0.055)
Lev	-0.236 ***	0.010	-0.092*
	(0.051)	(0.009)	(0.050)
ATO	-0.004	0.029	0.038
	(0.127)	(0.022)	(0.123)
Indep	0.770 ***	-0.032 ***	0.800 ***
	(0.023)	(0.004)	(0.023)
ROE	0.016*	0.002	0.024**
	(0.009)	(0.002)	(0.010)
Fixed	-2.176 ***	-0.098 ***	-2.160 ***
	(0.074)	(0.013)	(0.072)
AssetGrowth	0.009	0.000	0.018**

	(0.009)	(0.002)	(0.009)
PB	0.004 ***	0.001 ***	0.001
	(0.002)	(0.000)	(0.002)
Constant	1.035 ***	0.264 ***	0.869 ***
	(0.058)	(0.010)	(0.058)
N	11,428	10,972	10,972
r^2	0.647	0.793	0.666
timing	YES	YES	YES
individually	YES	YES	YES
Sobel test	11.65 ***		

5.6.3 Analysis of Mechanisms to Mitigate Information Asymmetry

Table 5-13 reports the results of testing the mechanism of information asymmetry in digital technology innovation affecting the green transformation and upgrading of manufacturing industry. The results of column (1) have been shown in the previous section. Column (2) shows the regression results of information asymmetry as an explanatory variable on digital technological innovation, and the regression coefficient is -0.047 and is significant at the 1% level, which indicates that digital technological innovation can significantly alleviate the problem of information asymmetry. Column (3) demonstrates the estimation results of putting information asymmetry into the benchmark regression model, and the regression coefficient of information asymmetry is significantly negative at 1% level, indicating that the mechanism effect of mitigating information asymmetry exists significantly. In order to ensure the reliability of the research results, this paper adopts the Sobel test for the channel of action. The Sobel test Z-value of the mechanism effect of information asymmetry is 19.06, and the P-value is less than 0.01, the mechanism effect of alleviating information asymmetry is established.

Digital technological innovation can build a data transparency system through big data, blockchain and other technologies and shape supply chain collaboration networks, thereby optimizing resource allocation efficiency and alleviating information asymmetry. The enhancement of information asymmetry can be achieved by enhancing information transparency and market incentives, which can promote the application of green technologies, optimize green investment portfolios and enhance the efficiency of environmental governance, thus promoting the green transformation and upgrading of the manufacturing industry.

Table 5-13 Test Results of Mechanisms to Mitigate Information Asymmetry

	(1)	(2)	(3)
variant	*GTFP*	*ASY*	*GTFP*

lnTec	0.028 ***	-0.047 ***	0.016**
	(0.006)	(0.004)	(0.006)
ASY			-0.258***
			(0.016)
Lev	-0.236 ***	0.109 ***	-0.208 ***
	(0.051)	(0.031)	(0.050)
ATO	-0.004	-0.016	-0.008
	(0.127)	(0.077)	(0.125)
Indep	0.770 ***	-0.068 ***	0.752 ***
	(0.023)	(0.014)	(0.023)
ROE	0.016*	-0.071 ***	-0.002
	(0.009)	(0.006)	(0.009)
Fixed	-2.176 ***	0.262 ***	-2.109 ***
	(0.074)	(0.045)	(0.073)
AssetGrowth	0.009	-0.006	0.007
	(0.009)	(0.006)	(0.009)
PB	0.004 ***	-0.019***	-0.001
	(0.002)	(0.001)	(0.002)
Constant	1.035 ***	-0.232 ***	0.975 ***
	(0.058)	(0.035)	(0.057)
N	11,428	11,427	11,427
r^2	0.647	0.754	0.656
timing	YES	YES	YES
individually	YES	YES	YES
Sobel test	19.06 ***		

6. Research Conclusions and Policy Recommendations

6.1 Conclusions of the Study

This paper selects Shanghai and Shenzhen A-share manufacturing enterprises from 2012 to 2023 as the research object. Firstly, it studies the relationship between digital technology innovation and green transformation and upgrading of manufacturing industry; secondly, it analyzes the difference of this influential relationship in different regions, industry factor intensity and government subsidy degree; finally, it empirically examines the role channels of lowering transaction costs, enhancing human capital and alleviating information asymmetry; through a series of empirical demonstrations, this paper draws the following conclusions:

(1) The regression coefficients of digital technological innovation are stable and positive, and remain

unchanged when control variables are included or excluded and when fixed or random effect models are used, indicating that digital technological innovation can effectively promote green transformation and upgrading of the manufacturing industry. (2) Further analyze the heterogeneity of the impact of digital technological innovation on the green transformation and upgrading of the manufacturing industry in different regions, factor intensity and government subsidy levels. (3) Digital technological innovation can reduce transaction costs, enhance human capital and alleviate information asymmetry to a certain extent, and then promote the green transformation and upgrading of the manufacturing industry.

6.2 Recommendations for Countermeasures

First, financial support should be strengthened. The Government should set up a special fund or strengthen financial support for digital technological innovation through such methods as financial subsidies. This not only includes direct funding for R&D projects, but should also cover loan subsidies and risk compensation mechanisms for small and medium-sized enterprises (SMEs) to reduce their innovation costs. The government can encourage banks and other financial institutions to increase credit investment in digital technology innovation enterprises by cooperating with financial institutions and establishing a risk-sharing mechanism. For example, special funds for science and technology finance should be set up to provide low-interest loans or loan guarantees to innovative enterprises, so as to ease their financial pressure.

Secondly, policies should be formulated according to local conditions. Taking into account the significant differences in the economic foundation and industrial structure of each other region, localities should be allowed to formulate specific implementation plans in accordance with their own actual conditions on the basis of the guiding opinions issued at the national level. The Government should conduct in-depth research on the economic development and industrial status of each region and formulate green transformation policies that are in line with local realities, so as to realize coordinated regional development.

Thirdly, we will promote cooperation among industries, universities and research institutes. Universities, research institutes and enterprises are supported in establishing long-term cooperation in joint research and development. The transformation of scientific and technological achievements into actual productivity can be accelerated through joint laboratories, technology transfer centers and other forms. The government should establish an industry-university-research cooperation service platform to provide one-stop services such as information exchange, project matching and talent training, and to promote the efficient integration and utilization of the resources of all parties.

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