Enterprise Digital Transformation and Green Innovation

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Abstract: In this paper, we select A-listed companies from 2011 to 2020 to conduct theoretical analysis and empirical research on the mechanism of action between the digital transformation of firms and green innovation. One of the key findings of this study is that digital transformation can significantly promote green business innovation, and the conclusion still holds after a series of robustness tests. Through an analysis of the mechanism of action, it is found that digital transformation can enhance green innovation by promoting the quality of firms' internal control. Upon closer inspection, it was found that the higher the level of disclosure of corporate environmental information, the more evident the promotive effect of digital transformation on green innovation. The results of the research provide suggestions for companies to improve their green innovation capabilities and promote green transformation.

1. Introduction

China's economic development is currently advancing gradually. At the same time, pollution levels are rising and environmental issues are becoming more prevalent. At the moment, China is the country that emits the most carbon dioxide. Continuous reliance on non-renewable resources has led to resource depletion and environmental damage, which has emerged as a significant barrier to economic growth. Implementing green transformation and development is therefore urgent. From this perspective, green innovation with the goal of efficient resource use and pollution abatement is not only an effective means of achieving high quality economic development, but also the key to achieving a win-win relationship between business economic efficiency and environmental protection accountability. However, because of the high uncertainty of green innovation activities spontaneously^[1]. The question of how to encourage firms to conduct green innovation activities and how to enhance their green innovation capabilities is of great importance to firms in achieving green transformation and the goal of "emission peak, carbon neutrality" of society as a whole.

Digital transformation has accelerated worldwide in recent years. The proliferation of new technologies like big data, artificial intelligence, and cloud computing has become a major force driving business transformation and industrial upgrading. Companies are using digital technology to achieve substantial changes in production patterns, business processes, and organizational structures. This not only reduces the cost of acquiring information from the firm but also improves the efficiency of internal management and decision-making within the organization, which endows firms with greater vitality. At the same time, the national "14th Five-Year Plan" clearly regards

elements such as digital economy as the key elements to achieving the goal of carbon neutrality, which shows that digital technology plays an important role in realizing my country's green transformation. Therefore, the discussion of issues like how the digital transformation of enterprises will affect the level of green innovation, and what the mechanism is, has important practical significance.

In comparison to the existing literature, the marginal contribution of this article may include the following aspects: Firstly, this paper draws on microdata from listed firms to link the digital transformation of firms with green innovation. The existing literature mostly focuses on the positive role of enterprise digital transformation in improving capital market performance^[2], improving the comparability of accounting information^[3], improving enterprise total factor productivity^[4], and improving corporate governance^[5]. There are few relevant literatures on digital transformation and green innovation. Secondly, based on the internal control quality perspective, the mechanism of the impact of digital transformation on green innovation is constructed, which provides new insight into the mechanism between two factors. Finally, based on an empirical test, this paper analyses heterogeneity in the impact of corporate digital transformation on green innovation on green innovation across features of environmental information disclosure and environmental regulation, to provide a benchmark for how to implement digital transformation to promote green business innovation under different conditions.

2. Theoretical Analysis and Research Hypothesis

The digital transformation of enterprises is the process of deep integration of digital technology and then brings comprehensive changes to enterprises. Digital transformation has accelerated the informatization process of enterprises, realized the transformation of enterprises to intelligent manufacturing through various emerging digital technologies, and enhanced the green innovation capabilities of enterprises. Firstly, the digital transformation of enterprises improves the efficiency of information collection and reduces the cost of information acquisition. Internet, big data, artificial intelligence and other related technologies have broadened the depth and breadth of information obtained by enterprises in the process of enterprise information collection^[5]. In this process, digital technology is conducive to enterprises to accurately understand the government's compliance requirements and consumers' needs in terms of energy conservation and environmental protection, which encourages enterprises to carry out green innovation activities according to the needs of stakeholders. Secondly, digital transformation enables information integration to break time and space constraint and optimize the allocation of resources between different regions or organizations^[6]. On the one hand, digital transformation improves the digital operation and management capabilities of enterprises, makes operations more intelligent, and reduces information asymmetry within the enterprise. The effective connection of production, sales and other links is conducive to the recombination of various production factors^[7], thereby optimizing the green innovation resources of enterprises. Therefore, this paper proposes hypothesis 1:

H1: Digital transformation can promote green innovation of enterprises

Based on the theory of the basic view of natural resources, the internal organizational elements of the enterprise such as green resources are the basis for the enterprise to carry out green innovation and build a sustainable competitive advantage^[8]. In the process of digital transformation, digital technology is highly integrated in all aspects of the enterprise, which promotes the transformation and innovation of the internal operation and management model, and has a profound impact on the quality of the internal control of the enterprise. Specifically, digital transformation is conducive to the implementation of the five elements of internal control. First of all, digital transformation provides a good environment for enterprises to carry out internal control. Digital

technology enables the information sharing of various functional departments within the enterprise, enhances borderless collaboration among employees, promotes business linkage between internal modules, and effectively alleviates internal information asymmetry^[9]. Secondly, technologies such as big data, blockchain, and the Internet of Things enable companies to identify risks more accurately, help management respond to problems in the production and operation process in a timely manner, and help take measures to avoid losses. Thirdly, digital transformation has effectively reduced the cost of implementing internal supervision by enterprises^[10]. The intelligence of internal supervision mechanism makes it possible to track and diagnose internal processes in real time, effectively avoiding bad behavior, thereby improving the quality of internal control.

Unlike ordinary innovation activities, green innovation has the characteristics of high cost and high risk, and the realization of green transformation needs a relatively complete internal system to guarantee. The existing literature shows that a high level of internal control quality can ensure the effectiveness of enterprises' innovation investment by reducing agency problems, mitigating information asymmetry problems, and reducing the implementation risk of innovation activities^[11]. The improvement of information asymmetry within the enterprise has enabled timely communication and feedback between relevant departments and business units within the organization to ensure effective and timely transmission of internal and external information^[12], providing beneficial conditions for the optimization of internal resource allocation of the enterprise. At the same time, whether the enterprise's green innovation capability is enhanced is mainly reflected by such activities as green patent application, production or sales of energy-saving products, etc. These activities are characterized by strong professionalism and high confidentiality. A high level of internal control helps enterprises identify the specific risks and systematic risks of the company, and determine whether there are risks and defects in all links of green innovation activities. Therefore, if the quality of internal control is high, enterprises will allocate innovation resources more effectively, control the risk of green innovation investment activities, timely supervise the implementation of green transformation, and improve the level of green innovation. Therefore, this paper proposes hypothesis 2.

H2: Digital transformation fosters green innovation by enhancing the quality of internal corporate control.

3. Research Method

3.1 Sampling

This paper selects A-share listed companies from 2011 to 2020 as the research sample, and performs the following processing on the collected data: (1) Remove financial and insurance companies; (2) Remove ST, *ST, PT enterprise samples; (3) Eliminate samples with missing data; (4) Perform shrinkage processing on all continuous variables by 1% up and down, and finally obtain 18,393 company annual sample observations. The data in this paper mainly come from the annual reports of listed companies, CSMAR and CNRDS.

3.2 Variables

1) Explained variable: Green innovation (GI). In this paper, we refer to Wang's research $(2021)^{[13]}$, and use the number of green patent applications by firms as a measure of firms' green innovativeness. Firstly, the number of patent applications may reflect firms' innovation performance over the course of the year, which is more reliable and stable than patent authorization data; besides, because of the "right-skewed" feature of green patent application data, this paper performs a log transformation.

2) Explanatory variable: Digital transformation (DT). This paper draws on the research of Wu (2021)^[2], uses the text analysis method to count the frequency of keywords related to the digital transformation of enterprises in the annual reports of listed companies. The total index of digital transformation is obtained by summing up the word frequencies of keywords.

3) Control variables: To improve the precision of the research, this paper refers to previous research and chooses some control variables: firm age (Age), asset to liability ratio (Lev), profitability (Roa), asset scale (Size), fixed asset ratio (Tan) and management expense ratio (Mf), Tobin Q value (Tobin Q) in addition to controlling for the year fixed effect and the individual fixed effect.

3.3 Model Setting

Consistent with the previous theoretical analysis, this paper implements the following benchmark regression model to test the hypothesis.

$$GI_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \sum_{i=2}^{n} \alpha_i Control + \sum Firm + \sum Year + \varepsilon_{i,t}$$
(1)

Among them, the explained variable is green innovation (GI), the core explanatory variable is digital transformation (DT), Control is the control variable, i represents the enterprise, t represents the year, Σ Firm is the individual fixed effect, Σ Year is the year fixed effect, $\varepsilon_{i,t}$ are the random error terms in the baseline regression model.

4. Analysis of empirical results

4.1 Descriptive statistics and differences between groups

4.1.1 Descriptive statistics

Descriptive statistics for the main variables in this paper are presented in Table 1. The average value of GI is 1.223, and the median value is 0, which indicates that the degree of GI of most firms is not high. The maximum value of DT is 5.147, the minimum value is 0, and the standard deviation is 1.397, which indicates that there are also significant differences in DT across the different firms in the sample.

Variable	Size	Average	Standard Deviation	Min	Median	max
GI	18393	1.223	1.485	0	0	5.425
DT	18393	1.303	1.397	0	1.099	5.147
Age	18393	17.977	5.563	4.000	18.000	32.000
Tan	18393	0.214	0.162	0.002	0.180	0.687
Roa	18393	0.037	0.062	-0.260	0.036	0.275
Mf	18393	0.093	0.076	0.009	0.075	0.469
Lev	18393	0.425	0.208	0.055	0.416	0.888
TobinQ	18393	2.039	1.331	0.863	1.602	8.690
size	18393	22.213	1.316	19.022	22.028	26.135

Table 1: Descriptive statistics of main variables

4.1.2 Difference test between groups

Table 2 reveals the results of the univariate tests. For the purposes of this paper, the sample firms are divided into two groups according to whether or not the firms engaged in digital transformation, and the between-group difference test is performed on the explained variables from the two sample

groups. There is a higher sample group of digitally transformed firms, and the mean difference is significant.

Whether to carry out digital transformation					
No Yes Mean					
(N=7150) (N=11243) Difference Tes					
GI	0.949		1.390	-20.175***	

 Table 2: Univariate test results

4.2 Correlation Analysis

The correlation coefficient analysis of the main variables presented in this paper is performed first to initially test the research hypothesis. The Pearson correlation coefficient matrix for each variable is presented in Table 3. In Table 3, the correlation coefficient between GI and DT is found to be 0.170, and is significant at the 1% level, indicating that the greater the degree of DT, the stronger the firm's GI capacity, which preliminary verified the hypothesis of the present study.

Table 3: Pearson correlation coefficient of each variable (N=18393)

	DT	GI	Age	Tan	Roa	Mf	Lev	TobinQ	Size
DT	1								
GI	0.170***	1							
Age	0.013*	0.031***	1						
Tan	-0.021***	-0.298***	0.010	1					
Roa	0.004	0.019**	-0.074***	-0.078***	1				
Mf	-0.099***	0.103***	-0.083***	-0.116***	-0.174***	1			
Lev	0.177***	-0.083***	0.174***	0.084***	-0.359***	-0.277***	1		
TobinQ	-0.138***	0.092***	-0.016**	-0.109***	0.115***	0.365***	-0.271***	1	
Size	0.401***	0.034***	0.176***	0.108***	0.003	-0.375***	0.518***	-0.429***	1

Note: indicate significant at 10%, 5%, and 1% levels respectively, the same below.

4.3 Regression Analysis

4.3.1 Benchmark regression results

The regression results for the baseline model are shown in Table 4. Column (1)-(4) reports the results of the addition of control variables, individual fixed effects, and year-fixed effects to the model, respectively. In each column, the DT coefficients are all positive and is significant at the 1% level, showing that DT can significantly enhance GI, and the hypothesis of the paper was tested.

4.3.2 Robustness check

PSM test: The DT takes the median, and the value is 1 when the sample size is larger than the median, otherwise the value is 0. We use variables such as profitability (Roa), management fees (Mf), Tobin Q (TobinQ) and asset size (Size) as covariates in calculating the propensity score, and use 1:1 nearest neighbour matching. Table 5 shows the results. The matching result satisfies the propensity score balancing hypothesis. Column (1) reports regression results following matching.

	(1)	(2)	(3)	(4)
Variable	GI	GI	GI	GI
DT	0.244***	0.078***	0.112***	0.044***
	(31.144)	(6.050)	(13.666)	(3.558)
Lev			-0.140**	-0.034
			(-2.105)	(-0.323)
Size			0.480***	0.417***
			(36.221)	(12.408)
Age			0.020***	-0.002
			(8.199)	(-0.046)
TobinQ			0.006	0.021**
			(0.854)	(2.231)
Tan			-0.066	0.222
			(-0.826)	(1.464)
Roa			-0.223	0.009
			(-1.536)	(0.053)
Mf			0.280*	0.294
			(1.916)	(1.436)
Constant	0.851***	0.626***	-9.880***	-8.441***
	(35.767)	(25.084)	(-36.221)	(-9.836)
Ν	18,393	18,393	18,393	18,393
R-squared	0.059	0.140	0.151	0.168
YEAR FE	NO	YES	NO	YES
FIRM FE	NO	YES	NO	YES

 Table 4: Benchmark regression results

Note: t value in brackets, the same below.

Table 5: PSM analysis results

Variable	Sample	average		T test	
variable	Matching	Test	control	T value	P value
Dee	Unmatched	0.03885	0.0356	3.59	0.000
Roa	Matched	0.03883	0.03854	0.32	0.745
Mf	Unmatched	0.09743	0.08911	7.43	0.000
1011	Matched	0.09735	0.09732	0.03	0.980
TobinQ	Unmatched	2.1127	1.9627	7.65	0.000
TODINQ	Matched	2.1113	2.0805	1.47	0.141
Size	Unmatched	22.295	22.130	8.53	0.000
Size	Matched	22.295	22.316	-1.05	0.293

Replacement of core explanatory variables: Drawing on the practice of Qi (2021)^[5], the DT measurement method is replaced by the ratio of the digital economy related part to the total intangible assets in the details of the intangible assets disclosed at the end of the year in the notes to the financial reports of listed companies (Dig_ratio). In column (2) of Table 6, we report the regression results after substituting variables. We can see that the results of the robustness tests of replacing the baseline regressors are basically consistent with the previous results.

Add interaction fixed effects: This paper controls the year fixed effects and individual fixed effects in the baseline regression, but there is still the possibility of missing some industry and time trends. Column (3) of Table 6 performs regression analysis after adding the industry-year interaction fixed effect to the model to reduce the problem of potential omitted variables.

Instrumental variable method: Learn from the practices of Li (2020)^[14] to construct instrumental variables(IV). Column (4) and Column (5) report the regression results from the two-stage least squares procedure, indicating that the results of the basic regression analysis were reliable.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	GI	GI	GI	DT	GI
DT	0.053***		0.046***		0.105***
	(3.561)		(3.693)		(5.816)
Dig_ratio		0.392***			
		(37.522)			
IV				0.091***	
				(20.334)	
Anderson canon.					4657.88***
corr. LM statistic					4037.88
Cragg-Donald Wald					6737.79
F statistic					0737.79
Control Variable	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year&Ind FE	NO	NO	YES	NO	NO
Ν	9,985	17,849	18169	18,176	18,176
R-squared	0.173	0.402	0.767	0.529	0.166

Table 6: Robustness test results

5. Influence Mechanism Test

While the preceding explanations provide rich empirical support for the impact of DT on GI, the mechanism has yet to be investigated. We will continue to explore the mechanism through which DT promotes GI. For this purpose, this paper selects the "internal control quality" channel for verification. In reference to Li et al.'s (2022)^[15] practice, the internal control index in the Dibo database serves as a measure of the internal control quality.

Drawing on the research results of Wen and Ye (2014)^[16] on the mediation effect, the following three models are constructed to verify the mediation mechanism:

$$GI_{i,t} = a_0 + a_1 DT_{i,t} + \sum_{i=2}^n a_i Control + \sum Firm + \sum Year + \varepsilon_{i,t}$$
(2)

$$ICQ_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \sum_{i=2}^n \beta_i Control + \sum Firm + \sum Year + \varepsilon_{i,t}$$
(3)

$$GI_{i,t} = \gamma_0 + \gamma_1 DT_{i,t} + \gamma_2 ICQ_{i,t} + \sum_{i=2}^n \gamma_i Control + \sum Firm + \sum Year + \varepsilon_{i,t}$$
(4)

In columns (2) and (3) of Table 7, we report the role of internal control quality between DT and GI. The results in column (1) are the the baseline regression. In column (2), the DT coefficient is equal to 0.078. It is significantly positive at the 5% level; the coefficient of DT in column (3) is 0.044, which is significantly positive at the 1% level, and the coefficient on the ICQ is 0.017, which is significantly positive at the 5% level. There is a significant positive relationship between the two variables. In short, it demonstrates that internal control quality plays an intermediary role between the DT and GI. Similarly, according to the test of the Boostrap mediation effect, the 95% confidence interval is found not to contain zero, and the P-value is significantly 0 at the 1% level indicating further support for the mediation effect of internal locus of control quality.

	(1)	(2)	(3)
VARIABLES	GI	ICQ	GI
DT	0.244***	0.078**	0.044***
	(31.144)	(2.315)	(3.507)
ICQ			0.017**
			(2.283)
Control Variable	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
N	18393	18,393	18,393
R-squared	0.059	0.082	0.168

Table 7: Mechanism test results

6. Further inspection

6.1 Environmental information disclosure

Positive environmental information disclosure reflects the environmental and social responsibilities undertaken by the enterprise, and conveys positive information about the green operation of the enterprise to the outside world ^[17]. The higher degree of environmental information disclosure reflects the enhancement of corporate social responsibility. It is conducive to the use of digital technology to identify and monitor pollution emissions and waste of resources in the production process, therefore carry out technological innovations such as energy conservation and emission reduction in a timely manner, and promote green innovative production of enterprises.

This paper draws on the practice of Kong et al. (2021)^[18] and uses the data of the environmental research database in CSMAR to measure the degree of corporate environmental information disclosure. Environmental information disclosure is a variable that can be used as a stand-in for environmental information disclosure by logarithmizing it to produce EDI. Column (3) of Table 8 reports the effect of environmental information disclosure on the relationship between DT and GI. The results show that the coefficient of the cross-product item is significantly positive, indicating that the higher the degree of environmental information disclosure, the more obvious that DT promotes corporate GI.

6.2 Environmental regulation

Environmental regulation is an important way for the government to exhort companies to keep the environment clean^[19]. Through the regulatory role of environmental regulation, firms are able to reduce the adverse impact of pollution emissions. Pollution abatement implies that firms should improve the efficiency of resource use. Flexible and targeted environmental regulations will drive firms' innovation activities^[20]. Based on the characteristics of high risk, high input and double externality of green innovation, it is difficult to produce effective driving effect by technology push and market pull model alone, while external environmental regulation is the original driving force of corporate green innovation^[21]. Companies with relevant digital technologies can accurately and efficiently gather information about green technologies in the presence of strong environmental regulations, optimising resource allocation over time, and are more likely to adopt green production processes in order to develop new energy saving and environmental protection products. This paper thus believes that the greater the degree of environmental regulation, the greater the role of DT in fostering GI.

According to Zhang and Chen (2021)^[22], this paper constructs proxy variables for environmental regulation (EV). Column (2) of Table 8 reports the role of environmental regulation in the DT and GI of enterprises. The finding demonstrates that the multiplier coefficient is highly positive, indicating that the encouragement of GI by businesses through DT will be more obvious if more stringently local environmental regulations are enforced.

6.3 Types of green innovation

In this paper, we divide green patents into green invention patents and green utility model patents, and investigate the impact of DT on different kinds of GI. Green invention patents have more prominent substantive features and significant progress with higher technical content, reflecting the quality of green innovation, while green utility model patents reflect the quantity of green innovation of enterprises. As can be observed from the results in Table 8 (3)-(4), DT promotes the effect of the production of green invention patents and green utility model patents, and more to

green invention patents. It shows that DT has a dual effect of "increasing quality and increasing quantity" on GI, and the effect of increasing quality is more obvious.

	(1) The Role Of Environmental information disclosure	(1) The Role Of Environmental regulation	(3)Green invention patents	(4)Green utility model patents
DT	0.044***	0.043***	0.046***	0.015**
	(3.486)	(3.429)	(6.623)	(2.114)
EDI	-0.008			
	(-0.446)			
DT×EDI	0.033***			
	(3.239)			
EV		2.807		
DT×EV		(0.174) 0.0481* (1.659)		
Control	YES	YES	YES	YES
Variable				
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
N	18393	18393	18,393	18,393
R-squared	0.169	0.168	0.144	0.124

Table 8: Further inspection results

7. Conclusion and Implications

In this paper, we take A-listed companies from 2011 to 2020 as the object of the research, we empirically test the impact and mechanism of the digital transformation of firms on green innovation.

To begin with, there is a link between digital transformation and green innovation. With the continued advancement of digital transformation, the efficiency of enterprise information gathering has steadily increased. Simultaneously, firms' internal and external resource allocation capabilities have been optimized in order to actively incentivize firms to engage in green innovation. In addition, the results of the mediation effect tests reveal that internal control quality is an intermediate factor for digital transformation to act on green innovation. The digital transformation of firms can increase the degree of internal quality of control, provide a supportive environment for green innovation, eliminate internal asymmetry of information, and decrease the risk of green innovation. Furthermore, this paper investigates the degree of environmental information disclosure, environmental regulations, and types of green innovation. It finds that the greater the degree of disclosure of environmental information and environmental regulations, the clearer the role of digital transformation in fostering green innovation. This paper advances the following policy recommendations based on the above views.

First, firms with suitable conditions should follow the digital economy's development trend and actively conduct digital transformation. Following the differentiation principle, firms of various types and industries should break through old production, manufacturing, and management models to meet their own development needs, decrease risks, and gradually raise the level of digital technology application. Besides, when conducting internal governance, enterprises must pay attention to the coordination and integration of digital technology and internal control systems, eliminate information and factor flow barriers, and build digital feedback systems, which can improve the quality of enterprise internal control. Furthermore, firms should aggressively publish

environmental information and capitalize on the positive role of environmental information disclosure in the interaction between digital transformation and green Innovation. Meanwhile, the government and other relevant departments must improve relevant laws and regulations, establish a sound environmental information management system, and improve environmental information disclosure standards and regulatory measures to promote green innovation and high-quality enterprise development.

References

[1] Zhou Xuefeng, Han Lu, Xiao Xiang. The Impact of Digital Economy on Enterprises' Sustainable Green Innovation under the "Double Carbon" Goal—Based on the Intermediary Perspective of Digital Transformation[J]. Securities Market Herald, 2022(11):2-12.

[2] Wu Fei, Hu Huizhi, Lin Huiyan, Ren Xiaoyi. Enterprise Digital Transformation and Capital Market Performance —Empirical Evidence from Stock Liquidity[J].Management World, 2021,37(07):130-144+10.

[3] Nie Xingkai, Wang Wenhua, Pei Xuan. Will the digital transformation of enterprises affect the comparability of accounting information [J]. Accounting Research, 2022 (05): 17-39

[4] Zhao Chenyu, Wang Wenchun, Li Xuesong. How Digital Transformation Affects Enterprise Total Factor Productivity [J]. Finance and Trade Economics, 2021, 42(07).

[5] Qi Huaijin, Cao Xiuqin, Liu Yanxia. The Impact of Digital Economy on Corporate Governance—Based on the Perspective of Information Asymmetry and Irrational Behavior of Managers [J]. Reform, 2020(04):50-64.

[6] Huang Dayu, Xie Huobao, Meng Xiangyu, etc. 2021. Digital Transformation and Enterprise Value: Empirical Evidence Based on Text Analysis Method [J]. Economist (12): 41-51.

[7] Liu Hui, Bai Cong. Has Digital Transformation Promoted Energy Conservation and Emission Reduction in Chinese Enterprises? [J]. Journal of Shanghai University of Finance and Economics, 2022, 24(05)

[8] Yang Dong, Chai Huimin. A review of the research on the driving factors of enterprise green technology innovation and its performance impact [J]. China Population Resources and Environment, 2015, 25(S2):132-136.

[9] Zhang Qincheng, Yang Mingzeng. Enterprise Digital Transformation and Internal Control Quality—A Quasi-Natural Experiment Based on the "Integration of Industrialization and Industrialization" Standard Implementation Pilot [J]. Audit Research, 2022(06):117-128.

[10] Gao Baoping. Enterprise Digital Transformation and Effectiveness of Internal Control [J]. Friends of Accounting, 2023 (04):127-133.

[11] Wang Yanan, Dai Wentao. Does internal control inhibit or promote enterprise innovation— Logic of China [J]. Audit and Economic Research, 2019, 34 (06): 19-32

[12] Wang Lei, Zhang Xiangli, Chi Guohua. The impact of internal control on bank credit risk - the intermediary effect of information asymmetry and agency costs [J]. Financial Forum, 2019, 24 (11): 14-23+54.

[13] Wang Xin, Wang Ying. Research on Green Credit Policy Promotes Green Innovation[J]. Management World, 2021, 37(06): 173-188+11.

[14] Li Tang, Li Qing, Chen Chuxia. The Influence Effect of Data Management Ability on Enterprise Productivity—New Findings from Chinese Enterprise-Labor Match Survey [J]. China Industrial Economics, 2020(06):174-192

[15] Li Yuan, Xue Yulian. Digital Transformation and Enterprise Sustainable Development[J]. Enterprise Economics, 2022, 41(12):61-68.

[16] Wen Zhonglin, Ye Baojuan. Mediation Effect Analysis: Method and Model Development[J]. Advances in Psychological Science, 2014, 22(05):731-745.

[17] Zhu Peng, Guo Wenfeng. The Impact of Environmental Information Disclosure Quality on Green Innovation[J]. Journal of Jishou University (Social Science Edition), 2022, 43(06):92-101.

[18] Kong Dongmin, Wei Yongxi, Ji Mianmian. Research on the Impact of Environmental Protection Fee Reform and Taxation on Enterprises' Green Information Disclosure [J]. Securities Market Herald, 2021(08):2-14.

[19] Greg Filbeck, Raymond F. Gorman. The Relationship between the Environmental and Financial Performance of Public Utilities [J]. Environmental and Resource Economics, 2004, 29(2).

[20] Liu Jinke, Xiao Yiyang. China's environmental protection tax and green innovation: leverage effect or crowding-out effect? [J] Economic Research, 2022, 57 (01): 72-88

[21] Xing Liyun, Yu Huixin, Ren Xiangwei. Network embeddedness, green dynamic capability and enterprise green innovation—the regulatory role of environmental regulation and managers' environmental attention [J]. Science and Technology Progress and Countermeasures, 2022, 39 (14): 105-113

[22] Zhang Jianpeng, Chen Shiyi. Financial development, environmental regulation and green economic transformation [J]. Financial Research, 2021, 47 (11): 78-93.