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The Impact of Digital Technology Integration on Low-Carbon Transformation in Energy-Intensive Enterprises: An Empirical Study Based on A-Share Listed Companies in Shanghai and Shenzhen

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Abstract. This paper selects panel data of A-share listed firms in energy-intensive industries from 2009 to 2021. It uses text analysis to count the frequency of digital-technology-related words in annual reports to measure the level of corporate digital technology integration, and adopts the LTFP method to evaluate the low-carbon transformation progress of energy-intensive firms. The paper empirically tests the effect and internal transmission mechanism of digital technology integration on green and low-carbon transformation. The results show that digital technology integration significantly promotes the low-carbon transformation of energy-intensive enterprises, and this conclusion remains valid after a series of robustness tests. Mechanism analysis indicates that digital technology integration boosts low-carbon transformation mainly by enhancing corporate R&D innovation capacity and reducing operating costs. Heterogeneity analysis reveals that the driving effect of digital technology integration is more prominent in large-scale firms, non-state-owned enterprises, and firms in central and western regions. Based on empirical findings, this paper puts forward targeted policy suggestions from two aspects: optimizing the external institutional environment and building internal corporate capabilities.

Keywords: Digital Technology Integration, Low-Carbon Transition, R&D Capabilities, Operating Costs, Energy-Intensive Enterprises

1. Introduction

China's energy conservation and carbon reduction in key industries have achieved phased results. Large enterprises play a leading role, the application of digital technology has accelerated, and the supporting policy system has been gradually improved. However, traditional energy-intensive sectors such as steel, chemical engineering and building materials still face practical constraints including insufficient R&D investment and high cost pressure during transformation. According to the National Science and Technology Expenditure Statistical Bulletin, the average R&D intensity of the above industries is generally below 2%, far lower than the national average. The transformation of energy-intensive enterprises has reached a critical juncture requiring breakthroughs.

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The rapid iteration of digital technologies including industrial internet, big data and artificial intelligence provides a new path for enterprises to optimize energy management, innovate production processes and achieve accurate carbon emission reduction. Through the deep integration of digital technology and the whole process of production and operation, enterprises can use digital platforms to monitor energy consumption data in real time, accurately identify pain points of energy use and formulate targeted energy-saving plans. Meanwhile, big data analysis and intelligent algorithms can optimize production processes, reduce ineffective energy consumption and carbon emissions in production links, and provide technical support for corporate carbon accounting and management. Against this background, this paper focuses on core questions: Can digital technology integration help energy-intensive enterprises achieve green and low-carbon transformation? What is its specific mechanism?

2. Literature review

2.1. Digital technology and its economic consequences

The development of information and communication technology has clarified the connotation of digital technology. Although academia has not formed a unified definition, it mostly defines its scope from functional and non-functional perspectives. As a general-purpose technology, digital technology can reduce the costs of information search, replication, transmission, tracking and verification in digital economic activities. It mainly covers artificial intelligence, big data, cloud computing, blockchain, integrated circuits and other fields, with the characteristics of self-learning, iterative upgrading and in-depth industrial integration, and can drive technological breakthroughs in downstream industries through its own innovation.

Compared with traditional information and communication technology, digital technology has three techno-economic characteristics: universality, substitutability and synergy. It can penetrate into economic activities such as production and consumption in non-digital fields, promote industrial digital transformation, and participate in value creation through substitution and synergy effects. It also has real-time and self-growth information processing advantages that traditional technologies do not have. However, the differences in digital resource endowment and technology application capacity have gradually widened the gap in digital technology value transformation among different industries.

Existing research on the economic effects of digital technology is abundant. Theoretically, most studies analyze the green value of digital technology in productivity growth, value chain upgrading and cost reduction from the perspectives of energy efficiency improvement and value chain restructuring. Empirical studies mostly use text analysis to measure digital technology and explore its economic impact on industries and enterprises. Dai Xiang and Yang Shuangzhi [1] found that digital technology empowers green transformation of manufacturing through scale effect and technology effect, and can produce positive spillover effects along the industrial chain. Tian Xiujuan and Li Rui [2] constructed a multi-sector Schumpeterian endogenous growth DSGE model, confirming that digital technology empowers real economy transformation by improving integration productivity and alleviating financing constraints. Kong Xiaorui et al. [3] verified based on provincial panel data that digital transformation promotes green and low-carbon development of manufacturing by adjusting energy consumption intensity, improving innovation capacity and optimizing energy consumption structure. Zhang Hanyu et al. [4] constructed corporate digital technology application indicators through text mining and machine learning, and found that digital

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technology application can improve corporate environmental performance through green innovation, financing constraint alleviation, management myopia inhibition and market signal enhancement.

2.2. Factors influencing low-carbon transformation in the industry

The core of industrial low-carbon transformation is enterprise low-carbon transformation. Existing studies analyze the driving factors of corporate green transformation from macro, meso and micro dimensions. At the macro level, the Porter Hypothesis proposes that environmental regulation can help enterprises build competitive advantages while improving environmental quality. At the meso industrial and enterprise network level, environmental regulation, technological innovation, financial support and international cooperation are the keys to industrial restructuring and environmental performance. At the micro enterprise behavior level, resource endowment, senior management team and green innovation capacity determine the implementation effect of corporate green transformation and innovation.

Theoretically, corporate low-carbon transformation is driven by multiple factors such as its own capacity, market pressure and government supervision. Existing studies discuss from the perspectives of resource capacity, market competition, policy incentive and media supervision. For energy-intensive industries, low energy efficiency, strict financing constraints, slow breakthrough of core technologies and extensive supply chain management are the main obstacles to green transformation. In terms of measurement, scholars have used ML-DEA, SBM-DDF-AAM [5], IPCC carbon accounting and other methods to evaluate the low-carbon transformation level of regions and industries.

2.3. Application of digital technologies and industry low-carbon transformation

There are many studies on the relationship between digital technology and low-carbon transformation, but academia has not yet formed a unified conclusion. Some scholars believe that digital technology can significantly accelerate corporate low-carbon transformation by promoting technological innovation, alleviating information asymmetry and reducing carbon emission externalities [6]. Other scholars hold the opposite view, arguing that digital technology may increase power consumption and carbon emissions while driving economic growth [7].

In summary, existing research has not reached a unified conclusion on the impact of digital technology on low-carbon transformation, and research focusing on energy-intensive industries is relatively limited. The marginal contributions of this paper are as follows: First, it explores the impact of digital technology integration on energy-intensive enterprises from a micro perspective. Second, it systematically deconstructs the driving mechanism and fills the research gap. Third, it optimizes the measurement method of low-carbon transformation by using the LTFP index.

3. Research hypothesis

3.1. The integration of digital technologies helps promote the green and low-carbon transformation of enterprises in energy-intensive industries

Li Guolan [8] defines green and low-carbon transformation of energy-intensive enterprises as a process guided by new development concepts, focusing on quality improvement, efficiency enhancement, energy conservation and carbon reduction, driven by green technological innovation, supported by green supply chain management, balancing environmental and economic benefits.

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Under the traditional development model, energy-intensive enterprises are constrained by resource supply, efficiency bottlenecks and technical barriers. Digital technology integration provides a new path by restructuring production processes and management models.

According to the theory of technological system integration, digital technology integration breaks technical islands, realizes collaborative complementarity of multiple technologies, and improves total factor productivity through data standardization and platform integration. It builds a full-life-cycle digital management system for energy and breaks data barriers between production, environmental protection and management. Based on system coupling theory, digital integration promotes the coordination of production, energy and environment systems. Accordingly, this paper proposes:

Hypothesis 1: Digital technology integration facilitates the green and low-carbon transformation of enterprises in energy-intensive industries.

3.2. Digital technology integration promotes the green and low-carbon transformation of energy-intensive industries by enhancing R&D capabilities

The core bottleneck of low-carbon transformation is the insufficient supply of green technology. Traditional R&D models face problems such as fragmentation, long cycles and difficult cross-domain cooperation. Digital technology integration builds an integrated R&D innovation platform, connects the whole chain from R&D design to achievement transformation, optimizes R&D processes, reduces experimental costs, and accelerates the commercialization of green innovation achievements. It can continuously strengthen the supply of clean production and energy-saving technologies, and promote enterprises to transform from high-consumption to low-carbon development. Accordingly, this paper proposes:

Hypothesis 2: Digital technology integration promotes the green and low-carbon transformation of energy-intensive enterprises by strengthening their R&D capabilities.

3.3. Digital technology integration promotes the green and low-carbon transformation of energy-intensive industries by reducing operational costs

Traditional energy-intensive enterprises face rising operating costs due to energy waste, low labor efficiency and extensive pollution control, which squeeze the space for green investment. Digital technology integration realizes precise management of energy, labor and pollution control costs. It reduces energy consumption through intelligent monitoring, cuts labor and management costs through automation, and lowers pollution control costs through digital early warning. Cost savings can be reinvested in green development, accelerating low-carbon transformation. Accordingly, this paper proposes:

Hypothesis 3: The application of digital technologies can promote the green and low-carbon transformation of energy-intensive industries by reducing operational costs.

4. Research design

4.1. Sample selection and data sources

According to the 2016 Statistical Bulletin issued by the National Bureau of Statistics, this paper selects six energy-intensive industries. It takes A-share listed companies from 2009 to 2021 as the research object. Referring to the 2012 industry classification standard of CSRC, 750 enterprises

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were initially screened, and financial industry, ST and data-missing samples were excluded. Finally, 261 enterprises and 3,272 firm-year observations were obtained. All continuous variables were processed by winsorization at 1% and 99%.

Corporate energy consumption data are from CEADs, EPS database and statistical yearbooks. Annual report data are from CSIRC, and financial indicators are from CSMAR.

4.2. Variable definition

(1) Dependent Variable: Low-carbon transformation (LTFP), measured by the Luenberger total factor productivity index. Inputs include capital, labor and energy; outputs include expected operating income and unexpected carbon emissions [9].

(2) Core Explanatory Variable: Digital technology integration level (lndigital), measured by the logarithm of digital keyword frequency in annual reports.

(3) Control Variables: Referring to Dai Xiang et al. [1] and Zhao Chenyu et al. [10], firm size (log of total employees), financial leverage (total liabilities/total assets at the end of the period), liquidity level (current ratio), firm growth (total assets growth rate), management shareholding ratio, independent director ratio, industry concentration (Herfindahl index), property right nature and capital intensity (net fixed assets/average annual employees) are selected as control variables.

4.3. Descriptive statistics for variables

Descriptive statistics show that the mean value of LTFP is 24.213, with a large gap between the minimum and maximum values, indicating significant differences in low-carbon transformation levels. The mean value of lndigital is 0.018, meaning that the overall digital integration level is relatively low. Other variables are within a reasonable distribution range.

Table 1. Descriptive statistics of variables

Variable	Obs	Mean	Std	Min	Max
LTFP	3198	24.213	40.341	-271.510	252.160
lndigital	3272	0.018	0.033	0.000	0.561
size	3270	8.073	1.148	3.135	11.168
leverage	3272	0.508	0.223	0.013	2.992
liquid	3272	1.533	2.087	0.047	54.357
growth	3272	0.407	11.885	-2.726	677.088
mshare	2795	0.068	0.161	0	1.532
Indep	3272	0.369	0.053	0.000	0.667
HHI	3272	0.119	0.080	0.036	0.654
nature	3272	0.609	0.488	0	1
cap_int	2915	2.186	2.427	0.257	44.678

4.4. Model configuration

To verify Hypothesis 1, a benchmark regression model is constructed:

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$$LTFP_{it} = \beta_0 + \beta_1 lndigital + \beta_i Controls_{it} + \lambda_i + \mu_i + \delta_i + \varepsilon_{it} \tag{1}$$

Among these, $LTFP_{it}$ is the dependent variable, representing the green and low-carbon transition status of energy-intensive firm i in period t; lndigitalt is the core explanatory variable, representing the digital technology integration level of energy-intensive firm i in period t; λ_i denotes the year fixed effect; μ_i denotes the province fixed effect; δ_i denotes the industry fixed effect; and ε_{it} is the random error term of the model.

To verify Hypothesis 2 and Hypothesis 3, mechanism test models of R&D capacity and operating cost are constructed respectively:

$$RD_t = \beta_0 + \beta_1 lndigital + \beta_i Controls_{it} + \lambda_i + \mu_i + \delta_i + \varepsilon_{it} \tag{2}$$

$$\mathrm{Cost_t} = \beta_0 + \beta_1 lndigital + \beta_i Controls_{it} + \lambda_i + \mu_i + \delta_i + \varepsilon_{it} \tag{3}$$

5. Empirical findings and analysis

5.1. Digital technology integration and green low-carbon transformation of energy-intensive enterprises

The benchmark regression results are shown in Table 2. The coefficient of lndigital is significantly positive at the 1% level, indicating that digital technology integration significantly promotes low-carbon transformation, supporting Hypothesis 1. Economically, a one-standard-deviation increase in digital integration improves the transformation level by about 3.976%. After adding control variables gradually, the core conclusion remains robust. Control variables are consistent with theoretical expectations.

Table 2. Digital technology integration and green low-carbon transformation of energy-intensive enterprises

Variable	(1)	(2)	(3)	(4)
	LTFP	LTFP	LTFP	LTFP
lndigital	6.475***	6.884***	6.735***	7.301***
	(0.614)	(0.623)	(0.624)	(0.669)
size		-1.597**	-1.720**	-3.680***
		(0.691)	(0.678)	(0.736)
leverage		10.847**	10.200**	10.220**
		(4.228)	(4.181)	(4.670)
liquid		-1.792***	-1.945***	-1.167**
		(0.527)	(0.518)	(0.578)

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Table 2. (continued)

lndep			-29.935***	-26.357**
			(10.908)	(11.478)
growth			8.986***	6.298***
			(2.051)	(1.984)
HHI			182.955***	173.170***
			(29.688)	(31.885)
Mshare				-48.094***
				(4.298)
nature				3.598**
				(1.733)
cap_int				-2.092***
				(0.533)
Constant	13.528***	22.788***	12.779	30.811***
	(1.096)	(6.063)	(8.202)	(8.592)
Obs	3,196	3,195	3,195	2,729
R^2	0.322	0.330	0.343	0.372
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; values in parentheses are robust standard errors. The same applies to all tables below.

5.2. Robustness test

This paper uses three methods to test robustness: variable replacement, one-period lag processing, and changing standard error clustering method. The results in Table 3 show that the coefficient of digital integration remains significantly positive, proving that the baseline conclusion is robust.

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Table 3. Robustness test results

Variable	(1) Replace Dependent variable	(2) Replace Explanatory variable	(3) One-period lag Processing	(4) Switch to standard error clustering method	
	Ltfp_ql	lndigital2	Ltfp_hl	Ltfp_hl	Ltfp_hl
lndigital	7.611***			7.301**	7.301***
	(5.88)			(3.25)	(3.67)
lndigital2		0.344***			
		(3.11)			
lndigital_lag1			7.559***		
			(10.66)		
Cluster by Firm				YES	
Cluster by Province					YES
Control			YES		
Constant	37.286*	29.403***	34.777***	30.811	30.811*
	(1.92)	(3.01)	(3.86)	(1.84)	(1.89)
Observations	2,729	2,414	2,581	2,729	2,729
R-squared	0.233	0.344	0.368	0.369	0.369
Province FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industy FE	YES	YES	YES	YES	YES

5.3. Discussion on endogeneity

To alleviate endogeneity problems, this paper selects three instrumental variables: lagged explanatory variable, peer average digital level, and number of landline telephones per 100 people in 1984. The first-stage F-values are all far greater than 10, rejecting the weak instrumental variable hypothesis. The second-stage results show that the core conclusion still holds, as shown in Table 4.

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Table 4. Results of endogeneity tests

Variable	Explanatory variable lagged by one period		The average level of digital technology integration among other enterprises in the same industry during the same year, excluding this enterprise.		Number of landline telephones per 100 people in 1984	
	(1) Phase One	(2) Phase Two	(3) Phase One	(4) Phase Two	(5) Phase One	(6) Phase Two
iv1	0.841*** (65.766)					
iv2			-1.642*** (-9.118)			
iv3					0.200*** (4.825)	
Control			YES			
Constant	0.025 (0.158)		2.189*** (5.998)		-0.116 (-0.422)	
Observations	2,58	2,579	2,792	2,729	2,352	2,299
F-values	4325.107		81.946		22.746	
R-squared	0.780	0.122	0.327	0.098	0.331	-1.197
Fire FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

5.4. Mechanism analysis

R&D capacity is measured by the number of corporate patents. The regression results show that the coefficient of digital technology integration is significantly positive at the 1% level, indicating that digital technology integration promotes low-carbon transformation by improving R&D capacity, and Hypothesis 2 is valid.

Operating cost is measured by operating cost. The regression results show that the coefficient of digital technology integration is significantly negative at the 1% level, indicating that digital technology integration promotes low-carbon transformation by reducing operating costs, and Hypothesis 3 is valid.

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Table 5. Digital technology integration and green low-carbon transformation of energy-intensive enterprises

Variable	(1)	(2)
	RD	Cost
lndigital	0.325***	-0.011***
	(13.11)	(-2.96)
Control	YES	
Constant	-3.367***	0.999***
	(-9.87)	(23.68)
Observations	2,788	2,792
R^2	0.540	0.348
Province FE	YES	YES
Year FE	YES	YES
Industry FE	YES	YES

5.5. Heterogeneity analysis

Heterogeneity tests are conducted from three dimensions: region, ownership and firm size. The results in Table 6 show that the driving effect is stronger in central regions, state-owned enterprises and large-scale enterprises. Central region enterprises have greater transformation potential; state-owned enterprises have more policy and resource support; large enterprises have stronger digital implementation capacity.

Table 6. Table 5 results of heterogeneity tests

	(1)	(2)	(3)	(4)	(5)	(1)	(2)
Variable	Eastern Region	Central Region	Western Region	State-owned enterprise	non-state-owned enterprises	large enterprises	Small and medium-sized enterprises
lndigital	4.396***	11.305***	3.498*	7.501***	6.787***	7.061***	6.090***
	(5.99)	(9.45)	(1.96)	(3.95)	(5.84)	(10.07)	(3.19)
Control				YES			
Constant	-24.174***	53.028***	15.383	0.778	-2.734	2.467	45.446
	(-2.65)	(3.62)	(0.83)	(0.04)	(-0.18)	(0.29)	(1.30)
Observations	1,506	819	870	668	1,220	2,687	508
R^2	0.336	0.388	0.449	0.635	0.340	0.377	0.409
Province FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

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6. Conclusions and implications

6.1. Research conclusions

First, digital technology integration significantly and positively drives the low-carbon transformation of energy-intensive enterprises. Second, enhancing R&D innovation capabilities and reducing operating costs are the core transmission mechanisms. Third, the driving effect is more prominent in central and western regions, state-owned enterprises and large-scale enterprises.

6.2. Policy implications

Government Level:Accelerate the construction of digital infrastructure such as industrial internet to lower the transformation threshold for energy-intensive enterprises.Introduce differentiated fiscal, tax and financial policies, increase R&D deductions and green credit support.Promote industry-university-research cooperation and talent training to provide intellectual support.

Enterprise Level:Formulate practical digital transformation strategies, carry out pilot projects first and then expand in an all-round way.Strengthen employee digital skills training and improve the digital literacy of the whole staff.Build green and low-carbon supply chains through digital tools and expand the market value of low-carbon transformation.

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