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Digital Transformation and Energy Consumption: Efficiency Gains or Cost Pressures?

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Abstract

Based on microdata from China's A share industrial listed enterprises during 2011–2022, this study empirically examines the causal effect of digital transformation on energy consumption intensity and its underlying transmission channels. The findings reveal that digital transformation significantly reduces industrial energy intensity, with more pronounced effects observed in firms with less distorted factor markets, higher internal control quality, and lower agency costs. Mechanism analyses demonstrate that enhancing total factor productivity serves as the key mediating channel through which digitalization achieves energy conservation. Furthermore, both external investor sentiment and internal green governance performance exert significant positive moderating effects on digitalization's energy-saving outcomes. This research provides novel empirical evidence for understanding the micro-level mechanisms driving industrial green transition through digital technologies.

Keywords: Digital transformation; energy consumption intensity; investor sentiment; green governance performance; total factor productivity

JEL Classification: O33; Q41; L60; Q56

1. Introduction

The advancement of digital transformation is driving a fundamental restructuring of global manufacturing. This restructuring is not solely driven by technological progress but has been forcibly accelerated by the intersection of multiple tensions – energy constraints, climate crises, geopolitical shifts, and supply chain reconfigurations (Murshed *et al.*, 2022). Concurrently, digital transformation, with its capabilities in “intelligent automation,” “operational visibility,” and “networked collaboration,” has rapidly taken center stage. The European Green Deal explicitly calls for redefining industrial resource efficiency through digital technologies, while Germany’s Industry 4.0 strategy has established dedicated funds to synchronize digital transformation with energy efficiency improvements. Technology firms such as Siemens, GE Digital, and Schneider Electric are promoting global industrial platforms under the slogan “data as energy.” Yet, does digitalization truly deliver the structural improvements in industrial energy consumption as anticipated? Is the relationship between digital transformation and industrial energy consumption intensity a “techno-fix pathway” or a concealed “structural transfer”?

Existing research exhibits significant divergence regarding the relationship between digital transformation and energy consumption intensity: Some scholars emphasize its role in reducing energy consumption intensity through optimized production processes and enhanced managerial efficiency (Teng and Shen, 2023; Wang and Shao, 2023; Zhang and Zeng, 2024), while others highlight potential negative impacts due to increased technological investment costs and short-term energy demand surges (Ren *et al.*, 2021; Zhao *et al.*, 2022). Notably, existing studies frequently neglect distinctions between dimensions of digital transformation – for instance, basic informatization and advanced intelligentization may exert divergent effects on energy consumption. From the efficiency optimization perspective, extensive research confirms that digital transformation significantly enhances energy efficiency. Specific mechanisms include: real-time monitoring and optimization of production processes reducing energy waste (Wen *et al.*, 2022), digital supply chain coordination lowering energy losses in logistics (Xu *et al.*, 2024), and big data-driven demand forecasting mitigating energy consumption from overproduction (Zhang *et al.*, 2024). Conversely, research from the cost pressure perspective reveals potential increases in energy consumption through three channels: sunk costs from technological upgrades (Lindley *et al.*, 2023), substantial energy inputs for digital infrastructure maintenance (Rasoulinezhad, 2022), and operational inefficiencies due to workforce skill mismatches (Ren *et al.*, 2021). Recent integrative frameworks attempt to reconcile these opposing views. Al Hadwer *et al.* (2021) propose the “technology–organization–environment” framework to analyze multidimensional

energy effects, whereas Li *et al.* (2024) emphasize the mediating role of absorptive capacity through dynamic capability theory. Despite theoretical advancements, empirical shortcomings persist: most studies remain confined to correlational analyses with limited exploration of micro-level mechanisms, and insufficient consideration of regional heterogeneity in energy structures and institutional environments.

This study examines China's Shanghai and Shenzhen A share listed industrial enterprises from 2011 to 2022, integrating corporate annual report text data with micro-level energy consumption metrics to construct a two-way fixed effects model. This approach systematically evaluates the effects of digital transformation on energy consumption intensity. By incorporating mechanism variables such as investor sentiment and green governance performance, the research investigates the synergistic interactions between market environments and internal governance. Heterogeneity analysis further reveals boundary conditions for technological empowerment, including factor market mismatch and agency costs, addressing the pivotal question: Does digital transformation act as a “catalyst” for energy efficiency optimization, or does it become a “cost burden” constrained by institutional frictions?

The empirical results of this study indicate that digital transformation has a significant inhibitory effect on the energy consumption intensity of industrial enterprises. This result is transmitted through the improvement of total factor productivity (TFP). Further research reveals that the external market environment and internal governance capabilities play important moderating roles in technological empowerment: investor sentiment accelerates technology diffusion by alleviating financing constraints, while green governance performance enhances energy-saving effects through institutional synergies. However, distortions in factor markets, low internal control quality, and high agency costs significantly weaken the inhibitory effect of digital transformation on the energy consumption intensity of industrial enterprises.

The theoretical contribution of this study lies in systematically revealing the multidimensional mechanisms through which digital transformation influences energy consumption intensity and its institutional constraints, offering new perspectives on the synergistic path of technological empowerment and green transformation in emerging economies. It also constructs a “market–governance–capacity” triadic synergy model, revealing the differentiated moderating mechanisms of investor sentiment, green governance performance, and internal control quality on the technological effects. Furthermore, the heterogeneity analysis highlights that the effectiveness of technological empowerment is highly dependent on factor mobility and governance structure optimization.

2. Theoretical Framework and Hypothesis Development

Theories of technological change and the resource-based view provide an important starting point for understanding the impact of digital transformation on corporate energy efficiency. By adopting new technologies, enterprises continuously optimize their production functions, thereby improving output efficiency without significantly increasing the input of other factors (Paramati *et al.*, 2022). Under traditional production paradigms, energy consumption has often been considered a “black-box variable”, with enterprises finding it difficult to monitor energy flows and efficiency boundaries in real-time. However, digital transformation shifts energy management from post – analysis to real – time response, and from vague decision-making to precise scheduling. This change is not an incremental improvement, but rather a paradigm shift: enterprises are now able to instantly diagnose “waste,” predict and provide early warnings for “overproduction,” and automatically correct “inefficient processes”. In short, digitalization enhances enterprises’ cognitive and intervention capabilities regarding energy usage, which naturally leads to lower energy consumption per unit of output” (Ren *et al.*, 2021). Based on this, we propose the following hypothesis:

H₁: *Digital transformation significantly reduces the energy consumption intensity of industrial enterprises.*

However, whether enterprises can translate digital transformation into actual improvements in energy efficiency does not solely depend on the technology itself, but is also influenced by both external financial market sentiment and internal governance structures (Liu *et al.*, 2023). Corporate decisions are made under uncertainty, and financial market sentiment is a clear expression of this uncertainty. Behavioral finance suggests that investor sentiment can affect a firm’s access to financing, capital costs, and even risk preferences (Jie and Lv, 2023). During periods when the capital market is generally optimistic about digital technologies, enterprises are often more willing to make forward-looking technology investments and increase their spending on digital platforms, smart hardware, and green infrastructure (Teng and Shen, 2023). This optimistic external sentiment provides enterprises with dual incentives: on one hand, the valuation premium and financing convenience offered by the market reduce the opportunity cost of digital transformation; on the other hand, with increasing emphasis on ESG (environmental, social, governance) performance indicators by investors, enterprises are more motivated to direct digitalization towards energy conservation and emission reduction, thereby strengthening their commitment to transformation in energy management. This suggests that investor sentiment is not merely an external variable, but may be a critical condition for whether enterprises can effectively utilize digitalization to enhance energy efficiency. Based on this, we propose the following hypothesis:

H₂: *Investor sentiment positively moderates the relationship between digital transformation and the energy consumption intensity of industrial enterprises.*

Furthermore, from an institutional theory perspective, corporate behavior is influenced by economic incentives, institutional norms, social expectations, and governance structures (Lee and Lee, 2022; Zakari *et al.*, 2022). Against the backdrop of increasing environmental awareness, green governance has become a critical institutional cornerstone for corporate decision-making, which in turn alters the direction and objectives of digital transformation. The same technology deployment, in enterprises with weak environmental governance, may be used to increase production capacity and reduce costs; while in companies with well-established governance mechanisms that prioritize long-term sustainability, it is more likely to be directed towards reducing emissions, optimizing energy structures, and improving resource efficiency (Bu *et al.*, 2022). In the context of global net-zero emission targets, industrial enterprises are facing increasingly stringent environmental regulations and market pressures, driving them to deeply embed green governance mechanisms into their digital transformation strategies (Murshed *et al.*, 2022). Research by Chang *et al.* (2023) shows that enterprises with robust green governance structures are more inclined to deploy digital technologies in energy monitoring, clean production, and other environmentally friendly applications, rather than solely focusing on expanding production capacity. This institutional constraint significantly alters the energy impact pathway of digital transformation: first, green governance strengthens the priority of energy efficiency goals by establishing a digital environmental performance evaluation system (Su *et al.*, 2022); second, it encourages enterprises to form organizational routines for “digital-green” synergistic innovation, thereby more effectively translating technological potential into actual energy-saving results (Zhao *et al.*, 2022). Therefore, we further propose:

H₃: *The level of corporate green governance positively moderates the relationship between digital transformation and energy consumption intensity.*

In addition to the external shaping of corporate behavior by institutional and market contexts, a deeper question arises: How does digital transformation function internally within enterprises and subsequently affect their energy usage logic? The deep application of digital technologies enhances TFP through three core channels: First, intelligent automation of production processes significantly reduces inefficiencies in factor allocation, bringing the technical ratio of energy input to output closer to the optimal frontier; second, data-driven precision decision-making optimizes the combination elasticity of capital, energy, and labor, achieving Pareto-improvement-type energy efficiency gains; finally, the cross-enterprise collaboration effects facilitated by industrial internet platforms amplify technologi-

cal spillovers, pushing the overall industry production function toward energy conservation (Zhang *et al.*, 2024). At the energy level, this leap in efficiency typically means a reduction in the energy required per unit of output. The reason digital transformation can significantly drive TFP growth is that it breaks through the “information bottlenecks” within enterprises: automated processes reduce inefficiencies caused by human intervention, data-driven resource allocation improves response accuracy at each production stage, and cross-departmental and cross-regional collaboration optimizes the operational rhythm of the entire supply chain (Wang *et al.*, 2025). These efficiency improvements are not confined to abstract organizational changes but are directly reflected in the improved efficiency of the use of physical resources such as energy and materials. Therefore, we propose the following:

H₄: Digital transformation reduces energy consumption intensity in industrial enterprises by improving TFP.

3. Research Methodology

3.1 Variable measurement

3.1.1 Dependent variable

Energy consumption intensity (*ECI*) reflects the energy utilization efficiency in the production process of industrial enterprises. Based on the studies of Wen *et al.* (2021) and Ju *et al.* (2024), various types of energy consumed by enterprises in the production process, such as water, electricity, and crude oil, are converted into standard coal equivalents. After calculating the total energy consumption, operating revenue is used as an indicator of economic output. The energy consumption ratio per unit of operating revenue is then constructed, and the natural logarithm is taken to eliminate heteroscedasticity. A lower energy consumption intensity indicates that the enterprise consumes less energy per unit of economic output, thereby demonstrating higher energy utilization efficiency.

3.1.2 Independent variable

Digital transformation (*Dig*). Following the approach of Gao *et al.* (2025), text analysis is employed. The study selects five core areas of digital technology – artificial intelligence, big data, cloud computing, blockchain, and general digital technologies – from the annual reports of listed companies. The frequency of the appearance of digital-related keywords in these areas is counted, and the natural logarithm of the sum of the keyword frequencies plus one is used to measure the degree of digital transformation.

3.1.3 Moderator variables

Investor sentiment (*Sentiment*) represents the collective psychological tendency of market participants regarding future asset values and risk expectations, reflecting investors' optimistic or pessimistic judgments about economic prospects, industry trends, and corporate performance. In this study, following Chau *et al.* (2016), we integrate four types of market behavior indicators – book-to-market ratio, stock return momentum, Tobin's Q, and stock turnover ratio. After removing the effects of fundamental factors such as firm size and profitability, we extract the residual volatility components and use principal component analysis to refine the first two principal components, which explain 85% of the cumulative variance. These components are then weighted to construct the *Sentiment* index.

Green governance performance (*GGP*) is used to measure a company's effectiveness and improvement in environmental governance. Following Wang and Xiao (2025), the Janis-Fadner (J-F) coefficient is used for calculation, considering both the positive and negative aspects of the company's green governance performance. The positive score (p) includes ISO 14000 certification, green awards, and compliance with pollution emission standards, with each criterion earning 1 point. The negative score (q) includes environmental administrative penalties, petition events, and non-compliance with pollution emission standards, with each criterion earning -1 point. The calculation formula is as follows:

$$GGP = \begin{cases} (p^2 - p \times |q|)/r^2, & \text{if } p > |q|, \\ (p \times |q| - q^2)/r^2, & \text{if } p < |q|, \\ 0, & \text{if } p = |q|. \end{cases} \quad (1)$$

where r is the sum of the absolute values of p and q . The *GGP* value ranges from $[-1, 1]$, with higher values indicating better green governance performance.

3.1.4 Mediating variable

Total factor productivity (*TFP*) is a core indicator of enterprise production efficiency, encompassing the nonlinear relationship between output levels and the input of production factors. Essentially, it reflects the additional output capacity driven by intangible factors such as technological advancement, management optimization, and resource allocation efficiency, after excluding the contributions of traditional factors. This study follows the approach of Melitz and Polanec (2015) and calculates *TFP* using the Olley-Pakes (OP) method. A higher *TFP* value indicates that an enterprise achieves higher output efficiency through technological upgrades or management optimization, given the same level of factor input.

3.1.5 Control variables

To control for the potential interference of firm heterogeneity on energy consumption intensity and mitigate omitted variable bias, this study follows the approach of Jing *et al.* (2025) and introduces the following control variables: leverage (*Lev*), intangible asset ratio (*Itang*), cash flow (*Cflow*), firm age (*Age*), ownership concentration (*Fir*), growth capability (*Growth*), asset turnover (*Turnover*), and fixed asset ratio (*Fixed*). These variables encompass multiple dimensions, including financial structure, firm characteristics, operational efficiency, and market dynamics, ensuring that the causal inference between *Dig* and *ECI* is more reliable. The definitions and calculation methods of these variables are detailed in Table 1.

Table 1: Variable definitions

Type	Name	Symbol	Definition
Dependent variable	Energy consumption intensity	<i>ECI</i>	$\ln(\text{Total energy consumption} / \text{Industrial output value})$
Independent variables	Digital transformation	<i>Dig</i>	$\ln(\text{Sum of digital transformation keywords frequency} + 1)$
		<i>Dig1</i>	$\ln(\text{Sum of digital transformation extended keywords frequency} + 1)$
Moderating variables	Investor sentiment	<i>Sentiment</i>	Composite index of investor sentiment
	Green governance performance	<i>GGP</i>	Calculated using the Janis–Fadner (J–F) method
Mediating variable	Total factor productivity	<i>TFP</i>	Calculated using the OP method
Control variables	Leverage	<i>Lev</i>	Total debt / Total assets
	Intangible asset ratio	<i>Itang</i>	Net intangible assets / Total assets
	Cash flow	<i>Cflow</i>	Net cash flow from operating activities / Total assets
	Firm age	<i>Age</i>	$\ln(\text{Years since the firm's listing} + 1)$
	Ownership concentration	<i>Fir</i>	Number of shares held by the largest shareholder / Total shares
	Growth capability	<i>Growth</i>	$(\text{Current year revenue} - \text{Previous year revenue}) / \text{Previous year revenue}$
	Asset turnover	<i>Turnover</i>	Operating revenue / Total assets
	Fixed asset ratio	<i>Fixed</i>	Net fixed assets / Total assets

Source: Authors' own elaboration

3.2 Empirical model

This study constructs the following two-way fixed effects model to examine the impact of digital transformation on energy consumption intensity:

$$ECI_{it} = \alpha_0 + \alpha_1 Dig_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (2)$$

where i and t represent the enterprise and the year, respectively. ECI_{it} is the dependent variable, energy consumption intensity, and Dig_{it} is the independent variable, digital transformation. Z_{it} represents the control variables of the enterprise. ε_i and μ_t are the industry and year fixed effects, respectively, and ϵ_{it} represents the error term.

3.3 Data sources

This study selects data from Chinese A share listed industrial enterprises between 2011 and 2022 as the research subject. The data primarily come from the CSMAR database, CNRDS database, Wind database, the *China Energy Statistical Yearbook*, and annual reports of listed companies. The research sample excludes ST and PT enterprises, firms with negative equity, and observations with missing key variables. Continuous variables are winsorized at the 1% percentile, and the final sample includes 17,492 valid observations.

4. Empirical Analysis

4.1 Descriptive statistics

According to the descriptive statistics in Table 2, there are significant differences in the distribution characteristics of ECI and Dig . The dispersion of ECI is relatively high, indicating substantial heterogeneity in energy utilization efficiency across enterprises. Its range of variation spans from extremely low to relatively high levels, reflecting the uneven energy management standards in the industrial sector. On the other hand, the distribution of Dig shows a right-skewed pattern, with most enterprises' digitalization levels concentrated in the lower to middle range. However, a small number of companies have digital practices that are significantly ahead, forming a long-tail distribution. This characteristic aligns with the staged penetration of digital technologies in the industrial sector. Notably, the median of ECI is slightly higher than its mean, while the mean and median of Dig are close, indicating that the former may have a few high-energy consumption outliers, while the latter has a relatively balanced overall distribution.

Table 2: Descriptive statistics

Variable name	Obs	Mean	SD	Min	Median	Max
<i>ECI</i>	17492	4.0495	1.3933	0.2702	4.2124	7.0857
<i>Dig</i>	17492	1.3108	1.2669	0.0000	1.0986	4.6913
<i>Dig1</i>	17492	2.2821	1.2525	0.0000	2.3026	5.0239
<i>Sentiment</i>	17492	0.0488	0.5539	−0.8558	−0.0548	1.9483
<i>GGP</i>	17492	0.6042	0.4442	0.0000	1.0000	1.0000
<i>TFP</i>	17492	6.7032	0.7755	4.9418	6.6179	8.7585
<i>Lev</i>	17492	0.4109	0.1882	0.0564	0.4087	0.8839
<i>Itang</i>	17492	0.0466	0.0402	0.0009	0.0369	0.2660
<i>Cflow</i>	17492	0.0548	0.0644	−0.1417	0.0517	0.2417
<i>Age</i>	17492	2.2643	0.6647	0.6931	2.3026	3.3322
<i>Fir</i>	17492	0.3352	0.1448	0.0876	0.3130	0.7306
<i>Growth</i>	17492	0.1563	0.3408	−0.4931	0.1054	2.3108
<i>Turnover</i>	17492	0.6236	0.3504	0.0949	0.5543	2.1626
<i>Fixed</i>	17492	0.2399	0.1445	0.0164	0.2111	0.6875

Source: Authors' own elaboration

4.2 Regression results

The baseline regression results in Table 3 show a robust negative association between digital transformation and energy consumption intensity. In column (1), where control variables are not included, the coefficient of *Dig* is significantly negative, indicating that the application of digital technologies is directly associated with improved energy efficiency. Further, in column (2), after introducing control variables related to corporate finance, operations, and governance, the coefficient of *Dig* remains significantly negative, suggesting that an increase in the level of digitalization systematically reduces energy consumption per unit of output. Specifically, for each 1 standard deviation increase in a firm's digitalization level, energy consumption intensity decreases by approximately 14.72%. This result supports the core argument of H_1 .

Table 3: Baseline regression results

	(1)	(2)
	ECI	ECI
<i>Dig</i>	−0.0918*** (−9.9493)	−0.1162*** (−17.6478)
<i>Lev</i>		−2.5767*** (−51.1827)
<i>Itang</i>		1.0856*** (5.2700)
<i>Cflow</i>		−3.4158*** (−25.3808)
<i>Age</i>		−0.5410*** (−43.9057)
<i>Fir</i>		−1.5960*** (−28.9357)
<i>Growth</i>		−0.2763*** (−10.6235)
<i>Turnover</i>		−1.2262*** (−43.8746)
<i>Fixed</i>		−0.4211*** (−6.4144)
<i>_cons</i>	4.1699*** (270.3640)	8.0666*** (208.9726)
Ind FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	17,492	17,492
adj. <i>R</i>²	0.0588	0.5227

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Values in parentheses are t-values (same below). FE stands for fixed effects.

Source: Authors' own elaboration

4.3 Mechanism analysis

4.3.1 Moderating effects

This study constructs a moderating effect model to explore the differentiated impact of the external market environment and internal governance capabilities on the energy-saving effects of digital transformation. The model is specified as follows:

$$ECI_{it} = \theta_0 + \theta_1 Dig_{it} + \theta_2 M_{it} + \theta_3 Dig_{it} \times M_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (3)$$

where M_{it} represents the moderating variables, including investor sentiment and green governance performance, and $Dig_{it} \times M_{it}$ represents the interaction term between digital transformation and the moderating variables.

Table 4 reports the moderating effects of *Sentiment* and *GGP* on the energy-saving effects of digital transformation. Column (2) shows that the coefficient of the interaction term $Dig \times Sentiment$ is negative and significant, indicating that market optimism enhances the inhibitory effect of digital transformation on energy consumption intensity. This result validates the key influence of the external market environment on the efficiency of technological empowerment, supporting H_2 .

The results in column (3) show that the coefficient of the interaction term $Dig \times GGP$ is significantly negative, indicating that enterprises with higher green governance performance can more effectively translate digital transformation into energy efficiency advantages. The improvement in green governance performance provides systemic support for the integration of digital technologies into energy management through institutional constraints and resource integration capabilities. This result confirms the moderating role of internal governance capabilities in the efficiency of technology conversion, supporting H_3 .

Table 4: Moderating effects

	(1)	(2)	(3)
	ECI	ECI	ECI
<i>Dig</i>	−0.1162*** (−17.6478)	−0.1121*** (−17.2615)	−0.0943*** (−9.5050)
<i>Sentiment</i>		0.1312*** (5.3422)	
<i>Dig × Sentiment</i>		−0.0518*** (−4.6564)	
<i>GGP</i>			−0.1916*** (−8.0545)
<i>Dig × GGP</i>			−0.0346*** (−2.6607)
_cons	8.0666*** (208.9726)	8.0537*** (208.7381)	8.1475*** (204.0559)
Controls	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
<i>N</i>	17,492	17,492	17,492
adj. <i>R</i>²	0.5227	0.5237	0.5282

Source: Authors' own elaboration

4.3.2 Mediation effect

This study further constructs a mediation effect model to examine the mechanism through which digital transformation impacts energy consumption intensity. The model is specified as follows:

$$TFP_{it} = \theta_0 + \theta_1 Dig_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (4)$$

$$ECI_{it} = \theta_0 + \theta_1 Dig_{it} + \theta_2 TFP_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (5)$$

The mediation effect test in Table 5 reveals that digital transformation impacts energy consumption intensity through TFP. The results in columns (1) and (2) show that *Dig* sig-

nificantly improves *TFP*, and the increase in *TFP* has a significant inhibitory effect on energy consumption intensity. This result confirms H4, which posits that digital transformation drives improvements in energy efficiency through the efficiency optimization pathway.

Table 5: Mediation effect

	(1)	(2)
	TFP	ECI
<i>Dig</i>	0.0354*** (10.0617)	−0.0608*** (−17.2023)
<i>TFP</i>		−1.5641*** (−175.9188)
<i>GI</i>		
_cons	4.8833*** (225.0646)	15.7043*** (343.1955)
Controls	Yes	Yes
Ind FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	17,492	17,492
adj. <i>R</i> ²	0.5442	0.8682

Source: Authors' own elaboration

4.4 Heterogeneity analysis

4.4.1 Factor market misallocation degree

The heterogeneity test in columns (1) and (2) of Table 6 is based on a group analysis of the degree of factor market misallocation. Following Chen *et al.* (2025), this study uses the factor market development index (*factor_{it}*) from the Fan Gang Marketization Index to calculate the relative gap between the factor market development level of each region and the highest value in the sample. The degree of factor market misallocation is defined as:

$$FAC_{it} = \frac{\max(factor_{it}) - factor_{it}}{\max(factor_{it})} \times 100 \quad (6)$$

This study divides the sample into high misallocation group (FAC_High) and low misallocation group (FAC_Low) based on the median. The results show that in the low misallocation group, the inhibitory effect of digital transformation on energy consumption intensity is significantly stronger than in the high misallocation group. This suggests that enterprises in areas with lower factor market distortions are more efficient at converting digital technologies into energy efficiency advantages. In low misallocation regions, reduced administrative intervention and credit distortions enhance factor mobility and the effectiveness of price signals, allowing enterprises to quickly integrate idle capacity and energy-saving technologies through digital platforms. On the other hand, in high misallocation regions, due to blocked factor flows, digital technologies are prone to falling into a “heavy investment, light collaboration” dilemma, making it difficult to unlock the systemic energy-saving potential.

4.4.2 Internal control quality

This study uses the DIB internal control index to divide the sample into high-quality group (IC_High) and low-quality group (IC_Low) based on the annual-industry mean. The results, as shown in columns (3) and (4) of Table 6, reveal that in the high-quality group, the inhibitory effect of digital transformation on energy consumption intensity is significantly stronger than in the low-quality group. This suggests that enterprises with higher internal control quality are more efficient in realizing the energy-saving potential of digital technologies. The underlying mechanism may stem from the fact that high levels of internal control enhance data governance capabilities and risk management mechanisms, reducing execution deviations and resource waste in technology applications. For example, enterprises with strict internal controls are more likely to deeply integrate digital systems into energy audits and performance evaluation processes, rather than merely focusing on automation at the equipment level. In contrast, low-quality enterprises, due to inconsistent management, are prone to the “digital silos” phenomenon, where technological investments fail to be converted into systemic efficiency improvements.

4.4.3 Agency costs

The heterogeneity test in columns (5) and (6) of Table 6 is based on a group analysis of agency costs. In this study, agency costs are measured by the management expense ratio, and the sample is divided into high agency cost group (AC_High) and low agency cost group (AC_Low) based on the annual-industry mean. The results show that in the low agency cost group, the inhibitory effect of *Dig* on *ECI* is significantly stronger than in the high agency cost

group. This suggests that enterprises with optimized governance structures can more efficiently unlock the energy-saving potential of digital transformation. This could be because enterprises with lower agency costs reduce conflicts of interest between management and shareholders, minimize non-productive resource consumption, and thus improve the focus of decision-making in the implementation of digital technologies. In contrast, high agency cost enterprises, due to decentralized decision-making, are more likely to experience a disconnect between technology applications and energy-saving goals, weakening the systemic effect of digital transformation.

Table 6: Heterogeneity tests

	FAC_High	FAC_Low	IC_High	IC_Low	AC_High	AC_Low
	ECI	ECI	ECI	ECI	ECI	ECI
Dig	−0.1181*** (−12.1962)	−0.1228*** (−13.4838)	−0.1147*** (−14.2863)	−0.1016*** (−9.4660)	−0.0840*** (−9.5267)	−0.1459*** (−16.7528)
_cons	7.8841*** (144.8019)	8.2452*** (147.6670)	8.0948*** (174.4391)	7.8040*** (117.4991)	7.8105*** (129.8707)	7.6403*** (156.7918)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8,812	8,680	11,238	6,254	6,860	10,632
adj. R²	0.5209	0.5364	0.5637	0.4485	0.4284	0.4850
Chow test	15.3688		210.4140		653.3964	
p-value	0.0000		0.0000		0.0000	

Source: Authors' own elaboration

4.5 Robustness tests

4.5.1 Endogeneity treatments

This study addresses potential endogeneity issues through the instrumental variable method to ensure the reliability of the conclusions. In Table 7, the mean digital transformation level of other enterprises in the same year and region is used as an instrumental variable.

The first-stage regression shows that *mean_Dig* has a significant positive effect on *Dig*, satisfying the relevance assumption. The Kleibergen–Paap test’s LM statistic significantly rejects the “weak instrumental variables” hypothesis, with the first-stage F–statistic exceeding the Stock–Yogo test critical value, thereby validating the effectiveness of the instrumental variables. In the second-stage regression, the coefficient of *Dig* is significantly negative, indicating that the inhibitory effect of digital transformation on energy consumption intensity remains robust, further supporting the conclusion of H_1 .

Table 7: Instrumental variable regression results

	First stage	Second stage
	ECI	ECI
<i>mean_Dig</i>	0.7730*** (29.4846)	
<i>Dig</i>		−0.2103*** (−6.7269)
Controls	Yes	Yes
Ind FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen–Paap rk LM statistic	749.4551***	
Kleibergen–Paap Wald rk F statistic	869.3425 [16.38]	
The <i>p</i>–value of the endogeneity test		0.0017

Note: The values in [] represent the critical thresholds for the Stock–Yogo weak instrument test at the 10% significance level.

Source: Authors’ own elaboration

4.5.2 Other robustness tests

This study further verifies the reliability of the inhibitory effect of digital transformation on energy consumption intensity by replacing variables, introducing regional fixed effects, and excluding the interference of low-carbon policies. The results are shown in Table 8. First, in column (1), an alternative measure of *Dig* is constructed using the Management

Discussion and Analysis (MDandA) text, where the frequency of digital-related keywords is counted across four dimensions: digital technology application, internet business models, intelligent manufacturing, and modern information systems. The coefficient of *Dig1* remains significantly negative, confirming that the conclusion is consistent across different measurement methods. Next, in column (2), regional fixed effects are added on top of the industry and year fixed effects. The coefficient of *Dig* remains significantly negative, which rules out the potential interference of regional resource endowment differences. Finally, since China has implemented the “Low-Carbon City Pilot” policy since 2010, there may be a confounding effect between policy-driven actions and corporate digital transformation. To clarify the independent effect of digital transformation, column (3) excludes the sample of enterprises from pilot cities, and the coefficient of *Dig* remains significantly negative, indicating that the energy-saving effect of digital transformation is not driven by passive responses to policy. In summary, the inhibitory effect of digital transformation on energy consumption intensity remains robust, consistent with H_1 .

Table 8: Other robustness tests

	(1)	(2)	(3)
	ECI	ECI	ECI
<i>Dig</i>		−0.1107*** (−16.4830)	−0.1093*** (−9.3561)
<i>Dig1</i>	−0.1406*** (−19.8513)		
_cons	8.2589*** (199.9508)	8.0139*** (203.3819)	7.6538*** (111.3985)
Controls	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Prov FE	No	Yes	No
<i>N</i>	17,492	17,492	6,175
adj. R^2	0.5254	0.5366	0.5164

Source: Authors’ own elaboration

5. Discussion

This study systematically examines the impact of digital transformation on energy consumption intensity and its underlying mechanisms using data from Chinese industrial enterprises. The research finds that digital transformation significantly reduces energy consumption intensity through efficiency optimization, with this effect being jointly moderated by market environment and corporate governance.

Firstly, the energy efficiency optimization effect of digital transformation is the core finding of this study. Digital transformation significantly lowers the energy consumption intensity of industrial enterprises, which is consistent with existing literature on the logic of “digital technology driving efficiency improvements” (Tang *et al.*, 2025). Moreover, the TFP improvement pathway shows that digital technologies reduce idle equipment losses through intelligent scheduling, supporting Melitz and Polanec (2015) theory that TFP drives efficiency improvement.

Secondly, the synergistic moderating effects of market environment and governance capabilities provide strong support for the energy-saving effects of digital transformation. The positive moderating role of investor sentiment suggests that optimistic sentiment accelerates the long-term penetration of digital technologies by alleviating financing constraints. This finding aligns with Ding *et al.* (2019) classic conclusion on “market sentiment amplifying short-term fluctuations”, emphasizing the role of the market environment. At the same time, the complementary moderating effect of green governance performance highlights the importance of the synergy between institutions and technology. Enterprises with higher green governance performance integrate digital technologies through institutional constraints, creating a synergistic effect between technology application and environmental responsibility. This result supports Yu *et al.* (2023) hypothesis that “environmental regulations promote technological conversion”, emphasizing the role of green governance in the sustainable development of energy enterprises.

Finally, the heterogeneity analysis underscores the importance of the factor market environment and firms’ internal governance structures. From a resource allocation perspective, enterprises facing lower market misallocation can more effectively recognize the value of digital technologies through price signals, thereby avoiding resource misallocation (Dong *et al.*, 2022). From a corporate governance perspective, high internal control quality and low agency costs reduce management’s short-term behavior, promoting long-term planning of digital investments. This conclusion complements Dong *et al.* (2024) research on “institutional quality affecting technology adoption outcomes”, showing that the energy-saving potential of digital transformation requires market-oriented reforms and corporate governance optimization as prerequisites.

6. Conclusion and recommendations

This study systematically investigates the impact of digital transformation on energy consumption intensity and its internal mechanisms based on data from China's Shanghai and Shenzhen A share listed industrial enterprises from 2011 to 2022, yielding the following conclusions: First, digital transformation significantly reduces the energy consumption intensity of industrial enterprises. Second, the external market environment and internal governance capacity have positive moderating effects on the energy-saving outcomes of digital transformation. Third, digital transformation reduces reliance on traditional energy – intensive technologies by enhancing total factor productivity. Fourth, heterogeneity analysis shows that the energy-saving effects of digital transformation are more significant in enterprises with low factor market misallocation, high internal control quality, and low agency costs.

Based on the above conclusions, this study proposes the following policy recommendations: First, it is important to strengthen targeted support for digital transformation and lower the barriers to technology adoption. For energy-intensive enterprises, the government can establish special funds to support the intelligent transformation of enterprises and implement tax incentives to reduce technology upgrade costs. Second, focus on the synergistic driving paths of TFP and green innovation. The government can promote “smart factory” benchmark cases through fiscal subsidies, guiding enterprises to adopt digital twin technologies to optimize resource allocation and establish industry-academia-research platforms to develop energy-saving algorithms. Third, optimize the synergistic mechanisms between market environment and corporate governance. Financial institutions should be encouraged to issue “digital green bonds”, linking energy-saving performance with financing costs to enhance capital market confidence in technological empowerment. Finally, corporate governance structures should be optimized to unlock the potential of technology. Internal control standards should be revised to incorporate digital energy-saving goals into senior management performance assessments.

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