Utilities Policy 82 (2023) 101542

Contents lists available at ScienceDirect

Utilities Policy

journal homepage: www.elsevier.com/locate/jup

Full-length article

Does digital transformation improve the operational efficiency of Chinese power enterprises?

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A R T I C L E I N F O

Handling Editor: Janice A. Beecher

Keywords:
Power enterprises
Digital transformation
Operational efficiency

A B S T R A C T

With the ongoing reform of the electric power system, more and more power enterprises are adopting digital transformation (DT) as a key strategy to stay competitive in the market. This study aims to examine the potential impact of DT on the operational efficiency (OE) of power enterprises, as well as to investigate the underlying mechanisms, which have received limited attention in prior research. Our findings suggest that DT indirectly improves the OE of power enterprises by promoting innovation, enhancing capital utilization rates, and easing financial constraints. Additionally, DT plays a more significant role in improving OE in a fiercely competitive industry environment. Finally, large, state-owned, and growing power firms have benefited more from DT than other types of firms.

1. Introduction

China has become the world's most prominent country in terms of power generation, with its power generation capacity expanding rapidly in recent decades (Wang et al., 2020b). Based on statistics from the National Bureau of Statistics, China's total power generation in 2000 amounted to 1.356 trillion kilowatt-hours, constituting 8.7% of the global power generation output. By 2021, this had increased to 8.534 trillion kilowatt-hours, representing 30% of the world's overall power generation output. Fig. 1 depicts the power generation structure of China in 2021. Overall, China's electricity is mainly derived from thermal power, accounting for 71.1%, followed by hydropower, wind power, nuclear power, and solar power, accounting for 14.6%, 7.0%, 5.0%, and 2.3%, respectively.

Like other industries, China's power industry faces fierce market competition. The power industry in China has undergone three major stages of reform. The first stage was from 1997 to 2001, when the State Power Corporation was established, marking the separation of government and enterprise in the power industry. The second stage was from 2002 to 2014, when the government proposed the "separation of power generation and grid, separation of main and auxiliary businesses, separation of transmission and distribution, and competitive bidding for electricity" policy. The third stage began in 2015 when the government proposed to "manage the middle and open both ends," further improving the market mechanism for power generation and sales. As power system reform continues to deepen, the power industry gradually moves from oligopoly to full market competition (Li et al., 2018). In this context, reducing costs and increasing efficiency have become key concerns for these companies' production management processes (Gnansounou and Dong, 2004; Wang and Chen, 2012). However, the continued rise in competitive pressure has led to the failure of traditional management models to meet the demand for refined management in power companies. Therefore, it is urgent to introduce new technologies or management approaches.

To better cope with the increasingly fierce market competition, more and more power companies have identified digital transformation (DT) as a key strategy for their development. The DT of China's power industry has undergone multiple stages, including informatization, datafication, and digitization. In the 1990s, Chinese power companies introduced information technology to achieve internal informatization and automation. Starting in 2000, with the advancement of power marketization and supply-demand structure adjustment, Chinese power companies faced a more complex and dynamic market environment. They shifted from informatization to datafication, introducing data analysis technologies and applications, strengthening data collection, analysis, and utilization, and improving decision-making accuracy and efficiency. Since 2010, Chinese power companies have transformed datafication to digitization, which has been driven by the emergence and rapid development of novel information technologies such as artificial intelligence, cloud computing, and the Internet of Things (Pan

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https://doi.org/10.1016/j.jup.2023.101542
Received 23 November 2022; Received in revised form 17 March 2023; Accepted 17 March 2023
Available online 28 March 2023
0957-1787/

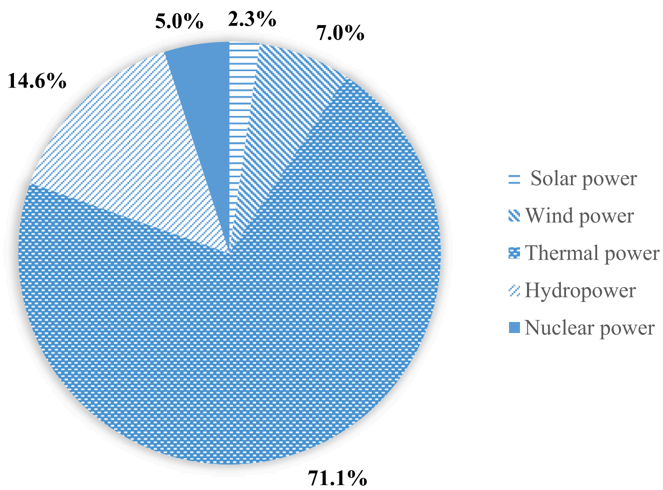

Fig. 1. China's power generation structure in 2021.

et al., 2020; Wen et al., 2022a; Zhang et al., 2022). With the widespread application of digital technologies in China's power companies, the technical characteristics of digitization, networking, and integration have been integrated into their work processes, greatly impacting their operations and management (Vu and Hartley, 2021). For example, emerging digital technologies related to intelligent power plants and grids, distributed power generation, and energy interconnectivity have emerged continuously, providing robust support for power companies in adapting to the intensely competitive environment.

DT has emerged as a critical means for enterprises to attain high-quality development, receiving widespread attention from researchers. However, there are still some limitations. First, in terms of research conclusions, there is still controversy about the impact of DT on corporate performance. Overall, most scholars believe that DT can enhance corporate performance (Ji et al., 2022; Peng and Tao, 2022), but some scholars also argue that the effect of DT on firm performance is not significant (Li and Jia, 2018; Usai et al., 2021). Recent studies have confirmed these concerns. The "China Enterprise Digital Transformation Index Report (2020)" pointed out that only 11% of companies that have implemented DT have achieved ultimate success. Therefore, more empirical evidence is needed to verify the relationship between them. Second, in terms of research content, most of these studies focus on innovation capabilities, financial performance, and other aspects, neglecting the impact of DT on corporate operational efficiency (OE), and the channels of influence are not yet clear. In addition, previous research on the performance of power enterprises has primarily focused on examining the influence of factors such as government subsidies, environmental regulations, and electricity market reforms (Bai et al., 2021; Dai and Wang, 2020; Wang et al., 2019, 2020b; Zhao and Ma, 2013). Limited research has specifically examined the effect of DT on the performance of power firms, and its role in power enterprises may be underestimated.

Furthermore, in terms of research perspective, existing studies mainly consider the impact of cross-sectional differences in enterprise heterogeneity from a static perspective, ignoring the impact of changes in industry competition structure and the potential heterogeneity of enterprises themselves over time. Industry competition has external governance effects and can play a screening role in selecting winners and eliminating losers (Chen and Chen, 2021). Industry competition determines enterprises' motivation to implement DT. In addition, the relationship between DT and OE may be dynamic and may vary as the enterprise moves through different stages of growth. Therefore, this study proposes the following research questions: **How does DT affect the OE of Chinese power enterprises? What are its potential impact mechanisms? Is the relationship between them subject to change as the degree of industrial competition and the life cycle stage of the enterprise change?**

This study addresses the research question by focusing on China's listed power generation companies and utilizes panel data from 2011 to 2020. First, text analysis is applied to determine the DT level of Chinese power generation companies, and the Super-SBM model is utilized to measure their OE. Second, the direct impact of DT on the OE of power generation companies is analyzed, and the underlying mechanism is revealed. In addition, the moderating effects of industry competition and company life cycle on this relationship are investigated. Finally, heterogeneity tests are conducted.

Compared to existing literature, this study makes several contributions. First, unlike previous research, this study focuses on the impact of DT on the OE of power companies based on micro-level data from China's power companies and clarifies its mechanism. The empirical findings of this study not only contribute to the existing studies on the determinants of power company performance but also serve to broaden the literature regarding the economic consequences of DT. Second, compared to previous studies, this research incorporates industry competition and company life cycle into the research model from the dynamic perspective of power companies' internal and external environment, thereby improving the research framework between DT and OE. Finally, the research conclusions of this study offer novel empirical evidence for the debate on whether DT can promote corporate performance. Our analysis provides valuable references for decision-makers seeking to optimize current mechanisms and allows for more effective leverage of the potential incentive effects of DT within the operation and management processes of China's power companies.

The remainder of this study is structured as follows: Section 2 comprises a comprehensive review of the relevant literature and an analysis of the theoretical mechanisms underpinning the research questions; Section 3 describes the data sources, variable selection, and research models employed in the study; Section 4 presents the empirical results and discussion. The study concludes with policy recommendations in the last section.

2. Literature review

2.1. Enterprise efficiency evaluation

In recent years, the evaluation of enterprise performance has garnered attention from numerous scholars (Ameer and Othman, 2012). The methods for evaluating enterprise performance consist mainly of parametric and non-parametric estimation techniques (Chen et al., 2015; Lin and Wang, 2014; Tajudeen, 2021; Wang et al., 2019).

Data envelopment analysis (DEA) is a prevalent non-parametric estimation method utilized in various fields (Ada et al., 2021; Izadikhah et al., 2022; Liu and Lin, 2018). Notably, one of the key benefits of DEA is that it does not necessitate any predetermined functional forms with regard to the inputs and outputs under consideration (Sueyoshi et al., 2020; Zhao and Ma, 2013). In 2001, Tone proposed the slacks-based measure (SBM), a DEA model that allows for varying scales of inputs and outputs (Tone, 2001). It is important to note that the efficiency value calculated using the SBM model is confined within the range of [0,1]. As such, a value of 1 for a decision-making unit (DMU) is considered incomparable. (Wu et al., 2021; Yu et al., 2019).

To address this limitation, Tone (2002) developed a modified mode known as the Super-SBM model, which enables secondary selection sorting of effective DMUs. This model has been widely used recently to measure enterprise efficiency (Dai and Wang, 2020; Lin and Xie, 2022; Wang et al., 2020a; Zhang et al., 2021). For instance, Wang et al. (2020a) used the Super-SBM model to examine the green innovation efficiency of 3557 companies from 2014 to 2017. Accordingly, in this study, we adopt the Super-SBM model to evaluate the OE of Chinese power companies to obtain more accurate assessment outcomes.

2.2. DT and enterprise performance

DT refers to a series of digital-oriented activities that companies use to upgrade and transform existing technologies, products, and businesses and improve competitiveness through digital technology (Gilch and Sieweke, 2021). In recent years, many enterprises have incorporated DT as a corporate strategy to inform decision-making and achieve structural optimization.

DT is a trend in technological change characterized by disruptive innovation, and it has been widely discussed in the literature. Existing studies on DT mainly focus on its influencing factors (Ghobakhloo and Iranmanesh, 2021) and economic consequences (Ji et al., 2022; Li and Jia, 2018; Peng and Tao, 2022; Usai et al., 2021). Despite the fruitful outcomes yielded by prior research, the influence of DT on enterprise performance remains controversial.

Most of the research shows that DT stimulates enterprise performance by optimizing the mode of operation management of enterprises, accelerating the flow of internal and external information, and alleviating information asymmetry (Ji et al., 2022; Peng and Tao, 2022). Promoting DT also helps enterprises build dynamic coordination ability to integrate resources, skills, and knowledge. For example, a recent study by Ji et al. (2022) indicated that DT could exert a substantial positive impact on the financial performance of Chinese manufacturing firms. Additionally, Peng and Tao (2022) reported that implementing DT can lead to notable improvements in the innovation performance of enterprises.

However, some scholars believe that DT has an insignificant effect on enterprise performance. These studies argue that DT generates additional costs, including learning and derivative management costs (Li and Jia, 2018; Usai et al., 2021). For example, Li and Jia (2018) revealed that adopting information technology alone cannot impact changes in enterprise performance and that resource arrangements need to be used to leverage the supporting role of information technology.

2.3. Theoretical mechanism

2.3.1. Improving innovation performance

Potentially, DT impacts power companies' innovation performance (Bhatti et al., 2021; Liu et al., 2022). First, power companies can utilize digital technology to collect and analyze massive amounts of data, providing ample data support for innovation (Liu et al., 2022). Second, by building digital platforms, more participants can be empowered to participate in innovation. Additionally, DT can bring more efficient collaboration and communication methods for companies, promoting the sharing of innovation resources and thus improving innovation performance. For example, the investigations conducted by Peng and Tao (2022) and Wen et al. (2022b) suggested that utilizing digital technology may effectively invigorate the innovation potential within organizations. Moreover, improvements in innovation performance enable power companies to respond more flexibly to on-site demands, optimize production processes, and reduce production costs, thus enhancing OE (Cuevas-Vargas et al., 2021; Herrera, 2016; Zhai et al., 2022). Therefore, DT can promote enterprise innovation, thus improving OE.

2.3.2. Promoting capital utilization rates

Improving capital utilization is a crucial objective in the process of DT (Peng and Tao, 2022), which can help power companies enhance their asset management, predictive maintenance, data analysis, and asset sharing, thereby increasing the utilization of their assets. Utilizing digital technologies, power companies can accurately monitor their assets' status, location, usage, and maintenance needs, optimize their allocation and utilization, and reduce idleness and waste. Meanwhile, improving the asset utilization rates can help enhance the OE of the enterprise (Andersen et al., 2012; Zhai et al., 2022). First, optimizing asset allocation and utilization can help companies reduce production and management costs and improve profit margins. Second, predictive maintenance can prevent downtime and production losses, ensuring production schedules and quality. Third, data analysis can help identify potential issues and opportunities, enabling companies to take timely improvement measures to enhance production efficiency and quality. Lastly, asset sharing can reduce the wastage of idle assets and increase asset utilization, thereby reducing enterprise costs. Therefore, DT can help improve capital utilization rates, indirectly enhancing the OE of companies.

2.3.3. Alleviating financing constraints

DT can alleviate financing constraints on power companies in various ways. First, applying digital technology in power companies increases the disclosure intensity of financial and credit information, helping financial institutions to identify high-quality companies, lower their credit risk costs, and make it easier for power companies to obtain loans (Lee et al., 2023). Second, DT helps improve power companies' production and management efficiency, thereby increasing their profitability and financial condition and attracting external investment. Additionally, under the national digital economy strategy, power enterprises can obtain more policy support from the government through DT (Luo et al., 2021), which can ease financing constraints. Finally, power companies can also take advantage of the benefits of digital information to timely obtain external financing information (Liu et al., 2022), which helps to overcome financing difficulties. At the same time, alleviating financing constraints provides more funding for power companies to optimize production processes and update equipment and technology, thereby improving their OE (Hai et al., 2022; Wu and Huang, 2022). Therefore, DT can help alleviate financing constraints, indirectly improving the OE of power companies.

In summary, DT can indirectly improve the OE of power enterprises by promoting innovation, improving capital utilization rates, and easing financing constraints.

2.4. The regulatory role of industrial competition and corporate life cycle

2.4.1. Industrial competition

Industrial competition, as the external environment of the enterprise, has a particular external governance effect (Chen and Chen, 2021). Industrial competition determines the impetus for firms to undergo DT (Liu et al., 2021), as changes in the competitive structure of the sector can influence the relationship between DT and OE. In a competitive market environment, power firms require more efficient and flexible management practices to adapt to market changes and competitive pressures, and DT is an effective means of achieving this goal. Thus, the intensification of industry competition prompts power enterprises to emphasize DT and accelerate the process of DT to improve OE.

2.4.2. Enterprise life cycle

The enterprise life cycle encompasses the complete process of an enterprise from naissance, development, maturation, and decline to death (Esqueda and O'Connor, 2020). The theory of the firm life cycle posits that firms differ significantly in scale, profitability, and growth in different stages of development (Arikan and Stulz, 2016). Thus, the impact of DT on OE is expected to vary across different lifecycle stages. Relative to mature and declining enterprises, growing power companies generally have more flexible and open management models, making it easier to absorb new ideas and technologies and integrate them into their operations to improve efficiency. Additionally, the organizational structures and business models of growing power companies are not yet fully optimized, necessitating better resource allocation to meet rapidly growing market demand and competitive pressure. DT can aid in the optimization of resource allocation and improve OE. Furthermore, growing power companies often have a smaller market share, and DT can aid them in comprehending market changes, adjusting strategies promptly, and better adapting to the competitive market environment.

3. Research design

3.1. Data sources

This study aims to investigate the impact of DT on the OE of Chinese power companies. A sample of Chinese-listed power generation companies from 2011 to 2020 is selected as the research subjects. The sample selection process consists of the following steps: (1) A preliminary list of power generation firms is determined based on the 2012 industry classification outlined by the China Securities Regulatory Commission. (2) Only enterprises related to power generation are retained. (3) Power generation companies already listed before 2011 are retained. (4) ST and *ST enterprises are excluded. (5) Samples with incomplete data are also excluded. (6) To meet the requirement of the Super-SBM model that the value of indicators must be no less than zero, samples with negative input or output indicators are further excluded. Ultimately, the study obtains a balanced panel data set containing 540 valid observations from 54 power generation firms. The data utilized in this study are derived from various sources, including the China Stock Market and Accounting Research Database (CSMAR), the China National Intellectual Property Administration (CNIPA), and corporate annual reports.

3.2. Selection of variables

3.2.1. Dependent variable

The dependent variable of our analysis is the OE of a firm, which is gauged using the Super-SBM model. We assume that there are m inputs, denoted by x_i $(i = 1, 2, 3 \ldots m)$, s outputs, denoted by y_r $(r = 1, 2, 3 \ldots s)$, in each MDU. We define the input and output slack of the variables, represented by s_i^-, s_r^+, respectively. The SBM model is structured as follows:

$$min\ \rho_1 = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{x_{ik}-s_i^-}{x_{ik}}}{\frac{1}{s}\sum_{r=1}^{s}\frac{y_{rk}+s_r^+}{y_{rk}}} \tag{1}$$

$$s.t.\begin{cases} x_{ik} - s_i^- \geq \sum_{j=1}^{n}\lambda_j x_{ij}, i = 1, \ldots, m \\ y_{rk} + s_r^+ \leq \sum_{j=1}^{n}\lambda_j y_{rj}, r = 1, \ldots, s \\ \lambda_j \geq 0, j = 1, \ldots, n \\ s_i^- \geq 0, i = 1, \ldots, m \\ s_r^+ \geq 0, r = 1, \ldots, s \end{cases}$$

where ρ_1^* is the objective function about the efficiency of DMU_k; $0 < \rho_1^* < 1$ indicates the current DMU is inefficient, and optimal efficiency is only achieved when $\rho_1^* = 1$ (He et al., 2018).

The Super-SBM model of the $\mathrm{DMU_k}$ is represented as follows. This model is advantageous because it allows for secondary selection sorting of effective DMUs.

$$min\ \rho_2 = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{x_{ik}+s_i^-}{x_{ik}}}{\frac{1}{s}\sum_{r=1}^{s}\frac{y_{rk}-s_r^+}{y_{rk}}} \tag{2}$$

$$s.t.\begin{cases} x_{ik} + s_i^- \geq \sum_{j=1\ ,\ j\neq k}^{n}\lambda_j x_{ij}, i = 1, \ldots, m \\ y_{rk} - s_r^+ \leq \sum_{j=1\ ,\ j\neq k}^{n}\lambda_j y_{rj}, r = 1, \ldots, s \\ \lambda_j \geq 0, j = 1, \ldots, n, j \neq k \\ s_i^- \geq 0, i = 1, \ldots, m \\ s_r^+ \geq 0, r = 1, \ldots, s \end{cases}$$

where the objective function about the efficiency of $\mathrm{DMU_k}$ is ρ_2^*, which is no less than 1. Thus, the super-efficiency value for $\mathrm{DMU_k}$ will remain at one even if $\mathrm{DMU_k}$ is inefficient (Liu et al., 2018). Thus, to determine whether $\mathrm{DMU_k}$ is efficient or inefficient, both Eqs. (1) and (2) must be employed (Lee, 2021).

The input indicators in this study include operating costs, net fixed assets, and the total number of employees, reflecting investment in management, capital, and human resources, respectively (Jiang et al., 2021a). The output variable is operating income, which reflects the operational capacity of the enterprise (Jiang et al., 2021a). The variables mentioned above are displayed in Table 1.

The evaluation results in column (1) of Table 2 indicate that the average OE of firms ranges from 0.401 to 1.324, with an average level of 0.664, demonstrating significant differences between firms, highlighting that the overall OE is low, deserving the attention of firms and the government. Furthermore, the average values of pure technical efficiency and scale efficiency, presented in columns (2) and (3), are 0.800 and 0.879, respectively, indicating that poor technology management and the inability to achieve scale effects are the main contributors to overall operational inefficiency.

3.2.2. Independent variable

The independent variable in our investigation is the degree of DT of Chinese power enterprises. Previous studies have widely adopted the textual analysis approach to measure DT (Chen and Hao, 2022; Zhao et al., 2022). These studies argue that text analysis using annual reports from listed enterprises effectively reflects the strategic orientation of firms. Drawing on these studies, we utilize a Python crawler to gather the annual reports of chosen samples from 2011 to 2020. Subsequently, we use the text analysis technique to extract all text contents. We obtain 79 related words, including digital financial, face recognition, intelligent robot, data mining, etc. Then, we employ the number of related words to represent the DT level of a firm (Chen and Hao, 2022; Zhai et al., 2022; Zhao et al., 2022).

3.2.3. Mediating variables

The mediating variables in this paper comprise innovation performance, capital utilization rates, and financing constraints. Given the data availability and the lagged impact of DT on innovation performance, we adopt the number of patents applied as a metric for measuring innovation performance, denoted as *IP*, in accordance with previous research (Kleis et al., 2012; Zhai et al., 2022; Zhao et al., 2022). In line with the study by Peng and Tao (2022), we choose total assets turnover to represent the capital utilization rates of firms, labeled as *TAT*. Additionally, to assess the degree of financial constraints, we utilize the SA index, labeled as *SA*, consistent with previous studies (Hadlock and Pierce, 2010; Zhao and Wang, 2022).

3.2.4. Moderating variables

The moderating variables in this paper are industrial competition and firm life cycle. We select the HHI index to measure industrial competition following previous studies, represented as *IC* (Dai et al., 2019; Yu et al., 2022). Notably, a smaller value of the HHI index indicates higher industrial competition (Dai et al., 2019). Moreover, referring to the study by Dickinson (2011), we adopt the method of cash

Table 1
Related indicators of OE measurement.

Aspects	Index	Unit	Mean	Std. Dev.	Min.	Max.	Source
Input indicators	Operating costs	Million yuan	10,878.453	20,760.910	106.029	150,659.440	CSMAR
	Net fixed assets	Million yuan	26,319.804	51,766.264	60.703	273,138.000	CSMAR
	Number of employees	Persons	5552.054	8492.651	172.000	58,263.000	CSMAR
Output indicators	Operating income	Million yuan	14,114.080	25,607.063	172.720	173,484.800	CSMAR

Table 2
Efficiency results for 54 power generation enterprises in China.

	(1) Operational efficiency	(2) Pure technical efficiency	(3) Scale efficiency
Mean	0.664	0.800	0.879
Min	0.401	0.418	0.380
Max	1.324	2.378	0.978

flow patterns to divide the lifecycle of these enterprises into growth, maturity, and decline periods. Therefore, we construct a dummy variable named *LC*. When an enterprise is in the growth stage, *LC* equals 1, and 0 otherwise.

3.2.5. Control variables

We also include the following control variables, which are consistent with existing studies on corporate performance (Chen and Hao, 2022; Coto-Millan et al., 2018; Jiang et al., 2021b; Ju and Liu, 2015; Song and Zhang, 2020): ownership concentration (*OC*), ownership (*OW*), enterprise-scale (*ES*), fixed assets ratio (*FA*), cash ratio (*CR*), and profitability (*ROE*). Table 3 presents the definitions of the main variables.

3.3. Regression model

Our primary objective is to assess the influence of DT on OE. Hence, we utilize a two-way fixed effects model to evaluate the direct impact of DT on OE (Chen and Hao, 2022). Our proposed baseline regression model is as follows:

$$OE_{i,t} = \alpha_1 + \beta_1 DT_{i,t} + Controls + \eta_i + \eta_t + \mu \tag{3}$$

where *i* is the firm, and *t* denotes the year. η_i and η_t refer to the individual fixed effect and time fixed effect, respectively. In addition, *Controls* represent the control variables included in our research model. μ is the error vector.

Subsequently, we introduce mediating variables (*IP*, *TAT*, *SA*) into the model to further explore the mechanisms through which DT affects OE. We construct the mediation effect models as follows:

$$IP_{i,t} = \alpha_2 + \beta_2 DT_{i,t} + Controls + \eta_i + \eta_t + \mu \tag{4}$$

$$TAT_{i,t} = \alpha_3 + \beta_3 DT_{i,t} + Controls + \eta_i + \eta_t + \mu \tag{5}$$

$$SA_{i,t} = \alpha_4 + \beta_4 DT_{i,t} + Controls + \eta_i + \eta_t + \mu \tag{6}$$

Finally, we test the moderating role of industrial competition level and firm lifecycle on the relationship between DT and OE by constructing the moderation effect models:

$$OE_{i,t} = \alpha_5 + \beta_5 DT_{i,t} + \beta_6 IC_t + \beta_7 DT_{i,t} \times IC_t + Controls + \eta_i + \eta_t + \mu \tag{7}$$

$$OE_{i,t} = \alpha_6 + \beta_8 DT_{i,t} + \beta_9 LC_{i,t} + \beta_{10} DT_{i,t} \times LC_{i,t} + Controls + \eta_i + \eta_t + \mu \tag{8}$$

4. Empirical results and discussion

4.1. Descriptive statistics and correlation analysis

Table 4 presents the descriptive statistics of the main variables. The range of *OE* values is from 0.303 to 3.062, suggesting significant variability in OE across these firms. Similarly, *DT* ranges from 0.000 to 4.190, indicating notable differences in the extent of DT among these firms.

Table 3
Definitions of the main variables.

Type	Variable names	Abbreviations	Measures	Source
Dependent variable	Operational efficiency	*OE*	The ratio of the operational activity input-output	CSMAR
Independent variable	Digital transformation	*DT*	Ln (the number of the vocabulary related to DT +1)	Corporate annual reports
Mediating variables	Innovation performance	*IP*	Ln (the number of patents applied+1)	CNIPA
	Capital utilization rates	*TAT*	Total assets turnover	CSMAR
	Financing constraints	*SA*	The SA index	CSMAR
Moderating variables	Industrial competition	*IC*	The HHI index	CSMAR
	Enterprise life cycle	*LC*	When an enterprise is in the stage of growth, *LC* = 1 and 0 otherwise.	CSMAR
Control variables	Ownership concentration	*OC*	The proportion of the first largest shareholder	CSMAR
	Ownership	*OW*	When an enterprise is a state-owned enterprise, *OW* = 1 and 0 otherwise.	CSMAR
	Enterprise-scale	*ES*	Ln (total assets)	CSMAR
	Fixed assets ratio	*FA*	Net fixed assets/total assets	CSMAR
	Cash ratio	*CR*	Cash and cash equivalents/ liabilities	CSMAR
	Profitability	*ROE*	Return on equity	CSMAR

4.2. Baseline regression

In line with the methodology of prior research (Chen and Hao, 2022), we employ a stepwise regression analysis to investigate the direct impact of DT on OE. The regression results are presented in Table 5.

The first column displays the regression results containing only independent variables, revealing a significantly positive coefficient of *DT* at the 1% level. It indicates that the OE of enterprises is positively

Table 4
Descriptive statistics of the main variables.

Variables	Obs.	Mean	Std. Dev.	Min	Max
OE	540	0.664	0.286	0.303	3.062
DT	540	0.598	0.814	0.000	4.190
IP	540	0.810	1.500	0.000	6.553
TAT	540	0.381	0.245	0.022	1.773
SA	540	−3.828	0.258	−4.430	−3.017
IC	540	0.081	0.006	0.072	0.090
LC	540	0.387	0.488	0.000	1.000
OC	540	40.688	15.636	10.569	83.433
OW	540	0.885	0.319	0.000	1.000
ES	540	9.634	1.472	6.414	12.990
FA	540	0.489	0.198	0.024	0.876
CR	540	0.403	0.530	0.007	5.542
ROE	540	0.067	0.143	−2.736	0.334

Table 5
Regression results of baseline.

Variable	(1) *OE*	(2) *OE*	(3) *OE*	(4) *OE*
DT	0.0652***	0.1069***	0.0811***	0.0614***
	(4.56)	(6.40)	(5.46)	(4.49)
OC			0.0098***	0.0070***
			(6.84)	(6.17)
OW			0.3371***	0.1409**
			(3.06)	(2.10)
ES			−0.0671***	−0.0294**
			(-3.13)	(-2.24)
FA			−0.8477***	−0.6956***
			(-10.06)	(-8.99)
CR			−0.0004	0.0127
			(-0.02)	(0.64)
ROE			0.1322**	0.2193***
			(2.18)	(3.50)
Constant	0.6248***	0.5999***	0.9697***	0.8205***
	(21.52)	(45.45)	(3.92)	(5.86)
Firm		YES	YES	
Year		YES	YES	
Hausman test			$\chi^2 = 58.66$, p = 0.0000	
R^2		0.567	0.674	
Obs.	540	540	540	540

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

influenced. To enhance the robustness of our findings, individual and temporal fixed effects, along with control variables, are gradually incorporated into the model. The second and third columns of the table reaffirm the significant and positive association between DT and OE, highlighting the robustness of our research. Furthermore, the fourth column displays the outcomes of the random effects model, which align with those of the third column. Based on the Hausman test results, the fixed effects model is a more suitable choice for our analysis.

4.3. Endogeneity issues

A prior investigation (Yu et al., 2020) indicated that government subsidies, which serve as an external source of financing for firms, have a noteworthy influence on their performance. In order to mitigate the influence of omitted variables, the study includes government subsidy intensity, denoted as *GS*, as a control variable. The regression outcomes are presented in the first column of Table 6. Additionally, the independent variable is lagged by one period to address potential endogeneity issues due to reverse causality, and the results are summarized in the second column.

To further address endogeneity issues, an instrumental variable (IV) approach is employed (Chen and Hao, 2022; Li and Lin, 2016). Referring to previous studies (Chen and Hao, 2022), the average industry-year level of DT by province is selected as an IV, labeled as *AV_DT*. On the one hand, as the level of DT in the industry increases, it will prompt companies to strengthen their DT levels to remain competitive. On the other hand, the construction of digital infrastructure and the development of a digital ecosystem within the industry will also facilitate the process of DT for companies. Therefore, there is a correlation between the level of DT in the industry and that of companies. Moreover, the level of DT in the industry does not directly impact individual company performance, so it satisfies the exogeneity requirement as an appropriate IV. The results of the first-stage regression are presented in the third column, with an F value of 38.71 (>10), indicating that there is no weak instrument problem (Chen and Hao, 2022). The second-stage results, shown in the fourth column, confirm the research conclusions of the study after addressing endogeneity issues.

Furthermore, following Goldsmith-Pinkham et al. (2020), the Bartik IV is constructed to address endogeneity issues. This IV is determined by the initial level of DT of a company and the growth rate of DT level in the industry, which is correlated with the level of DT of the company and is not related to the error term (Hasan et al., 2020). The Bartik IV has been shown in previous research to effectively address endogeneity issues caused by omitted variables and reverse causality (Goldsmith-Pinkham et al., 2020; Hasan et al., 2020). The outcomes of the first and second-stage regressions are displayed in columns (5) and (6), respectively. These findings validate the robustness of the research conclusions.

4.4. Robustness test

4.4.1. Potential collinearity

Based on the outcomes of the multicollinearity test, the mean-variance inflation factor (VIF) of the primary variables is 1.20 (<10), and the maximum VIF is 1.30 (<3.3). These findings indicate that our research model does not suffer from severe multicollinearity issues (Chen and Hao, 2022).

4.4.2. Eliminating the influence of outliers

To reduce the influence of outliers on the regression outcomes, we apply winsorization to the continuous variables by capping extreme values at 1% and 99% quartiles. The findings are presented in the first column of Table 7.

4.4.3. Substitution of the model

Given that the value of *OE* is positive, we employ a Tobit model to re-examine the regression outcomes (Ervural et al., 2018; Lin and Chen, 2020), as presented in the second column. Subsequently, drawing on the studies by Lee et al. (2022) and Lin and Zhu (2019), we utilize a system-GMM model to validate our research findings, and the outcomes are summarized in the third column. Remarkably, the estimation outcomes of these distinct models all demonstrate the robustness of our research conclusions.

4.4.4. Alternative indicators

We use the replacement of the independent variables approach to investigate the robustness of our findings further, as outlined in the study by Chen and Hao (2022). Drawing upon the research of Zhai et al. (2022), we create a dummy variable named *DT_DUM*, which takes a value of 1 when the value of *DT* for a given enterprise is greater than zero, and 0 otherwise. The findings presented in column (4) correspond to those in column (3) of Table 5, providing further support for the robustness of our findings.

4.4.5. Shortening the sample window

Considering the widespread outbreak of the COVID-19 pandemic in 2020, it is plausible that it may have influenced the decision-making regarding DT and the OE of firms. To avoid the interference of the COVID-19 pandemic on the research results, we shift our sample window to the period between 2011 and 2019. The regression results, presented in the fifth column, demonstrate the robustness of our research conclusions.

Table 6
Results of the endogeneity tests.

Variable	(1) *OE*	(2) *OE*	(3) *DT*	(4) *OE*	(5) *DT*	(6) *OE*
DT	0.0803***			0.0710***		0.2736***
	(5.38)			(2.99)		(2.96)
L.DT		0.0945***				
		(5.83)				
AV_DT			0.9913***			
			(17.36)			
Bartik					1.1088***	
					(4.00)	
OC	0.0099***	0.0109***	0.0059*	0.0099***	0.0035	0.0093***
	(6.85)	(6.92)	(1.68)	(6.86)	(0.71)	(4.94)
OW	0.3397***	0.3394***	0.1448	0.3373***	0.1249	0.3054**
	(3.08)	(3.03)	(0.54)	(3.06)	(0.35)	(2.34)
ES	−0.0674***	−0.0685***	0.0472	−0.0662***	0.1012	−0.0887***
	(-3.14)	(-2.98)	(0.91)	(-3.07)	(1.40)	(-3.06)
FA	−0.8427***	−0.9405***	−0.7077***	−0.8570***	−0.8748***	−0.7541***
	(-9.92)	(-10.41)	(-3.50)	(-9.96)	(-3.10)	(-5.63)
CR	0.0000	0.0038	−0.0341	−0.0003	0.0487	−0.0007
	(0.00)	(0.18)	(-0.73)	(-0.02)	(0.73)	(-0.03)
ROE	0.1351**	0.1194**	0.1661	0.1340**	0.0685	0.1038
	(2.22)	(1.97)	(1.13)	(2.21)	(0.36)	(1.45)
GS	−0.3210					
	(-0.49)					
Constant	0.9690***	0.9875***	−0.4703	0.9172***	−0.5992	1.1092***
	(3.91)	(3.70)	(-0.81)	(3.83)	(-0.73)	(3.59)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
F-value			38.71		11.70	
R^2	0.674	0.699	0.5685	0.3464	0.2961	0.1650
Obs.	540	486	540	540	486	486

Note: ****p < 0.01, **p < 0.05, *p < 0.1.*

Table 7
Results of the robustness tests.

Variable	(1) *OE*	(2) *OE*	(3) *OE*	(4) *OE*	(5) *OE*	(6) *OE*
DT	0.0533***	0.0811***	0.0561***		0.0393***	0.0127**
	(3.99)	(5.85)	(8.08)		(2.80)	(2.34)
DT_DUM				0.0746***		
				(3.34)		
L.OE			0.7513***			
			(54.27)			
OC	0.0071***	0.0098***	0.0023***	0.0103***	0.0081***	0.0025***
	(5.45)	(7.34)	(4.31)	(7.03)	(5.99)	(4.32)
OW	0.2838***	0.3371***	0.1390***	0.3153***	0.4906***	0.0879***
	(2.93)	(3.28)	(7.86)	(2.80)	(3.71)	(2.75)
ES	−0.0736***	−0.0671***	0.0183*	−0.0662***	−0.0780***	0.0244***
	(-3.86)	(-3.35)	(1.80)	(-3.02)	(-3.89)	(2.81)
FA	−0.7640***	−0.8477***	−0.5573***	−0.9218***	−0.7466***	−0.3720***
	(-10.31)	(-10.78)	(-11.19)	(-10.87)	(-9.64)	(-8.21)
CR	−0.0045	−0.0004	−0.0132	0.0033	−0.0131	0.0158***
	(-0.17)	(-0.02)	(-1.60)	(0.17)	(-0.77)	(3.60)
ROE	0.7826***	0.1322**	0.0973	0.1365**	0.6224***	0.0028
	(6.20)	(2.34)	(1.29)	(2.21)	(5.39)	(0.59)
Constant	1.1167***	0.7911***	−0.0621	1.0112***	0.9576***	0.3130***
	(5.10)	(3.06)	(-0.70)	(4.00)	(3.90)	(4.00)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.717			0.661	0.731	0.660
AR (1)			0.0007			
AR (2)			0.4084			
Sargan test			0.4327			
Obs.	540	540	486	540	486	1690

Note: ****p < 0.01, **p < 0.05, *p < 0.1.*

4.4.6. Changing the sample size

Given that our research sample only comprises power generation enterprises, we seek to expand our investigation and explore the impact of DT on the entire power industry. As such, we include power equipment listed companies in our study, using the same screening process as previously described. The regression findings in the sixth column provide evidence that our research outcomes remain robust even after enlarging the sample size.

4.5. Mechanism analysis

From the results reported in column (1) of Table 8, it is evident that the regression coefficient of *DT* is statistically significant, with a positive estimate that is significant at the 5% level, implying that DT promotes

Table 8
Regression results for the mechanism analysis.

Variable	(1) *IP*	(3) *TAT*	(3) *SA*
DT	0.1389**	0.0250**	0.0071**
	(2.35)	(2.26)	(2.04)
Constant	4.1074***	2.9133***	−3.7719***
	(4.17)	(15.78)	(-64.98)
Control	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
R^2	0.812	0.753	0.978
Obs.	540	540	540

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

innovation success. Hence, we conclude that innovation performance is a channel through which DT affects OE. The regression outcomes presented in column (2) indicate that the coefficient of *DT* is positively significant. Thus, capital utilization rates form the transmission mechanisms between DT and OE. As revealed in column (3) of the regression results, it can be observed that DT exerts a positive effect on alleviating financing constraints. Therefore, we can conclude that financing constraints mediate between DT and OE. These empirical results are consistent with theoretical mechanism analysis.

4.6. Moderating effect

We incorporate two moderating variables into our research model to examine the relationship between DT and OE. The first moderating variable is industrial competition, for which we construct the interaction term of $DT \times IC$ and include it in our research model, as shown in Eq. (7). Notably, a smaller value of *IC* indicates higher industrial competition. As depicted in column (1) of Table 9, the significantly negative coefficient of $DT \times IC$ suggests that increasing market competition may strengthen the impact of DT on OE.

In addition, we consider enterprise life cycle as another moderating variable and create the interaction term of $DT \times LC$, which is incorporated into our research model as depicted in Eq. (8). The findings presented in column (2) show that the coefficient of $DT \times LC$ is significantly positive, implying that DT has a greater impact on enhancing the OE of enterprises in the growth stage compared with the mature and declining stages. The findings of the full model, presented in column (3), further confirm the robustness of our results.

4.7. Heterogeneity analysis

4.7.1. Ownership

The samples are stratified into two distinct ownership types: state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs). The corresponding regression results for the two sub-samples are reported in the first and second columns of Table 10, respectively. The table illustrates that the estimated coefficient of *DT* is statistically significant and positive in the SOE group, whereas in the NSOE group, the coefficient of *DT* is not statistically significant. This finding implies that state-owned power enterprises benefit more from the process of DT in their operational performance than non-state-owned power enterprises.

Table 9
Regression results for the moderating effect.

Variable	(1) *OE*	(2) *OE*	(3) *OE*
DT	0.7312***	0.0631***	0.7008***
	(4.51)	(3.76)	(4.29)
$DT \times IC$	−8.2476***		−8.0533***
	(-4.02)		(-3.92)
$DT \times LC$		0.0439**	0.0368*
		(2.23)	(1.89)
Constant	0.8987***	0.9659***	0.8903***
	(3.68)	(3.91)	(3.65)
Control	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
R^2	0.684	0.678	0.688
Obs.	540	540	540

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.7.2. Enterprise size

The samples are partitioned into two groups based on the total number of employees, specifically the large enterprise (LE) group and the small and medium enterprise (SME) group. The outcomes of the regression analysis for the two sub-samples are presented in columns (3) and (4) of the table, respectively. The regression results suggest that the estimated coefficient of *DT* is statistically significant and positive for the LEs, whereas for the SMEs, the coefficient of *DT* is positive but does not demonstrate statistical significance. These findings imply that the effect of DT on the OE of LEs is more pronounced compared to SMEs.

5. Conclusion and policy implications

5.1. Discussion and conclusion

The present study concentrates on 54 listed power generation firms in China and employs the Super-SBM model to measure OE. Subsequently, an empirical investigation is conducted to assess the influence of DT on OE. The primary conclusions of this research can be summarized as follows:

First, the study reveals significant discrepancies in OE among the 54 listed power generation enterprises in China. The average observed OE of the sample enterprises during the studied period is low, indicating considerable scope for improvement. The study attributes this operational inefficiency to inadequate technology management and the failure to realize scale effects. Similar findings have been reported in recent research. For instance, Zhao and Zhen (2019) observed that the wind power industry in China exhibits low levels of OE. In another study, Gao et al. (2022) identified substantial potential for enhancing the OE of China's coal power generation firms.

Second, the findings suggest that DT has a significant positive effect on the OE of Chinese power firms, which remains robust after accounting for endogeneity and conducting various robust analyses. Moreover, the mediation analysis results reveal that implementing DT enhances innovation performance, promotes capital utilization rates, and alleviates financing constraints, thus indirectly promoting the OE of power firms.

Additionally, the influence of DT on the OE of Chinese power firms is contingent upon two factors: the degree of industrial competition and the life cycle stage of firms. Specifically, faced with intensified market competition, power firms are expected to benefit more from adopting DT strategies. Furthermore, the impact of DT on enhancing the OE of power firms is more pronounced in the growth stage than in the mature or decline stage. This observation is consistent with previous research by Wen et al. (2022b), which suggested that DT plays a more crucial role in

Table 10
Results of the heterogeneity analysis.

Variable	(1) SOEs	(2) NSOEs	(3) LEs	(4) SMs
DT	0.0846***	−0.0560	0.0322**	0.0399
	(5.41)	(-1.13)	(2.22)	(0.83)
Constant	1.2266***	−1.2671	1.8672***	0.4696
	(5.78)	(-1.37)	(6.95)	(0.76)
Control	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R^2	0.694	0.701	0.782	0.712
Obs.	477	62	429	108

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

enhancing the performance of firms in their growth phase.

Finally, the study reveals that the impact of DT on OE varies across different types of power enterprises. Specifically, state-owned power enterprises benefit more from DT than non-state-owned power enterprises, as DT can optimize resource allocation and leverage their advantages. Additionally, large power enterprises benefit more from DT than small and medium-sized power firms due to their financial, scale, and research and development advantages. These findings are consistent with previous studies, such as Ren et al. (2023) and Zhao et al. (2022), which suggested that SOEs and LEs are more likely to benefit from DT due to their inherent advantages.

5.2. Policy suggestions

(1) The findings of this study imply that DT is a vital factor in enhancing the OE of power enterprises. Therefore, policymakers should consider increasing investment in digital infrastructure, including the development of 5G networks and industrial internet, to support the DT of enterprises. Additionally, the government should facilitate a conducive external environment for innovation, enabling the mediating effect between DT and OE to be fully realized. Furthermore, the government needs to improve the subsidy mechanism for DT and reduce barriers to entry for venture capital institutions, thus addressing the financing constraints and high costs faced by power enterprises. Finally, enterprises ought to proactively promote the adoption of digital technology, accelerate technological change, and leverage technological leadership to achieve economies of scale, thereby improving their overall performance.

(2) Policymakers should implement dynamic incentive mechanisms which can adapt to the changes in competition levels within the power industry. With intensified competition in the industry, the government should increase support for digital technology adoption, encouraging power enterprises to optimize their organizational structure and business processes, innovate management modes, and achieve transformation and upgrading. Furthermore, the enterprise life cycle should be considered to enhance the effectiveness and precision of incentive policies for DT. The government ought to implement differentiated incentive policies, prioritize support for firms in the growth stage, and reduce the cost of DT, thereby improving the digital level of these enterprises.

(3) Policymakers should adopt targeted policies for digital industrial development and implement precise measures based on the resource endowment of power firms. To promote the coordinated development of power enterprises with different ownership and various sizes, the government should formulate DT policies that are tailored to the specific needs of each type of power enterprise, ensuring the policies' applicability and effectiveness. Encouraging collaboration among different types of power enterprises through policy guidance can also help to advance DT and enable high-quality development of the power industry through digitalization.

5.3. Research limitations

This study also has several limitations that warrant discussion. First, although the text analysis method used in this study can effectively capture the importance of digital technology to power enterprises, it may not fully reflect the actual level of DT and its impact on OE. Future research can address this limitation by developing a comprehensive index incorporating digital strategy, inputs, and outputs to systematically evaluate the DT level among power enterprises. Second, due to data availability constraints, this study only examines a limited sample of 54 listed power generation enterprises in China. Future research can expand the sample size by collaborating with more enterprises to obtain comprehensive data and verify our study findings. Lastly, the study period of this paper is relatively short, which may limit the generalizability of our findings over a longer time horizon. Future research can extend the sample period to obtain a more comprehensive and robust understanding of the impact of DT on OE in the power industry.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

We really apricate Professor Janice A. Beecher for editing our paper. This paper was supported by the National Natural Science Foundation of China [Key Program, grant numbers 72133003].

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