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The Impact of New Energy Enterprises' Digital Transformation on Their Total Factor Productivity: Empirical Evidence from China

Yangjun Ren [1,*], Xin Zhang [2] and Hui Chen [3]

[1] School of Economics and Trade, Changzhou Vocational Institute of Textile and Garment, Changzhou 213164, China
[2] Business School, Changzhou University, Changzhou 213164, China
[3] Department of Education, Nanjing University, Nanjing 210008, China
* Correspondence: 2019125@cztgi.edu.cn

Abstract: As digital technologies disrupt one sector after another, an increasing number of new energy enterprises are positively embracing digital transformation. However, it remains unclear whether digital transformation drives enterprise total factor productivity. To fill this gap, using a dataset of Chinese A-share listed new energy enterprises from 2009 to 2021, we investigate theimpact of digital transformation on a firm's total factor productivity. The results show that there is a promoting effect of digital transformation on new energy enterprises' total factor productivity. The promoting effect is significant only in the state-owned firms and the eastern region. Further, we demonstrate that when a firm has digital transformation, it has a higher operating efficiency, lower cost, and greater innovation power leading to higher total factor productivity. This research elucidates the role of digital transformation in fostering the new energy industry's growth and provides meaningful suggestions for improving the effectiveness of digital transformation in new energy enterprises.

Keywords: digital transformation; total factor productivity; new energy enterprises; China

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1. Introduction

In the last decade, a fresh impetus for economic growth has been provided by the boom in the digital economy [1]. The scale of the digital economy in 47 major economies reached USD 38.1 trillion in 2021, showing a growth rate of 15.6% per year [2]. Specifically, the United States and European Union have depended on cutting-edge technologies to build the digital economy's worldwide advantages [3]. The evolution of the digital economy has a long history [4]. As early as the 2008 financial crisis, the digital economy, powered by advanced digital technologies, has been growing and evolving [5–7]. In 2021, Germany, the United Kingdom and the United States ranked as the top three in terms of the share of the digital economy scale in GDP, all exceeding 65% [2]. As a developing country, China views it as a vital component of high-quality economic growth and supply-side structural reform, and has made clear arrangements in the 14th Five-Year Plan to accelerate the building of the digital economy, digital society, and digital government. From 2012 to 2021, China's digital economy increased annually by 15.9%, reaching USD 7.1 trillion by 2021 and becoming the world's second largest [2].

With the growth of the digital economy, a growing number of firms have responded to the trend and experienced digital transformation with the assistance of new technologies [3]. Digital transformation, as a process arising from the adoption of numerous modern technologies for data collection, storage and analytics, such as artificial intelligence, robotic automation, the Internet of Things, cloud computing and digital platforms, has become a strategic choice for most enterprises to improve operating efficiency, reduce cost and enhance innovation success [8–10]. When facing profound changes in technology and the market environment in the new digital economy, an increasing number of Chinese companies use digital tools and platforms to promote organizational change and accelerate the innovation of products and services, providing a new endogenous growth impetus for China's economic development [10]. According to the White Paper on the Digital Economy of Chinese Listed Companies (2022) released by the China Listed Companies Association, there were more than 1000 listed companies with the digital economy as their core industry in 2021, covering almost all industries [11].

To fulfill the rising energy demand, China has to expand its energy imports, resulting in an ever-increasing reliance on the international energy market, which affects China's economic growth, social stability, and energy security [12,13]. As a result, not only does the Chinese government confront energy-related risks, but also environmental pollution challenges [14]. In September 2020, the Chinese government announced that it would attain peak carbon emissions in 2030 and achieve carbon neutrality by 2060. Nevertheless, achieving such an ambitious target without sacrificing economic performance is still very difficult. However, the emergence of a new energy industry provides an excellent opportunity to address these issues. China is rich in clean new energy resources such as solar, biomass, and wind [12]. In recent years, governments at all levels have developed a variety of supporting policies, such as subsidy policies and green credit policies, to encourage the growth of the new energy industry. At present, the digital industry is becoming a new engine for economic transformation and upgrading. Digital transformation as a vehicle to drive structural change and promote low carbon development in the energy industry is both a real and urgent need and a direction for development in the industry. Under this background, accelerating the integration of the digital economy withthe new energy industry's development is becoming an effective way to accelerate the realization of the new energy industry's high-quality development. As a microcomponent of the macroeconomy, enterprises are the leading carrier forboosting the digital economy [4]. In addition, according to neoclassical economic growththeory, total factor productivity (TFP) is a crucial driver of economic progress [8]. Thus, digital technology should be used throughout the whole process of new energy industry's development to fully realize the digital transformation of new energy enterprises, improving new energy enterprises' total factor productivity [15,16]. However, the new energy industry's digital transformation has many weaknesses in infrastructure, application services, and digital technologies [17,18], resulting in a low degree of integration between the digital economy and new energy industry. In addition, the digital transformation of enterprises is essentially a systematic process to enhance the effectiveness of data flow with the help of cutting-edge digital technologies, such as big data, cloud computing, the Internet of Things, blockchain and artificial intelligence, which can strengthen core market competitiveness [19,20]. From this perspective, the digital transformation of enterprises is a long-term process, which is often realized through multiple methods of optimization and coordination, such as technological change, organizational change and resource change. According to the China Digital Transformation Index Report (2021) published by Accenture, only 16% of enterprises achieved significant results in digital transformation [21]. Therefore, a fundamental question arises: Has digital transformation promoted the total factor productivity of new energy enterprises?

This research aims to answer the question of to what extent digital transformation improves new energy enterprises' total factor productivity from a new perspective, because it is essential for the modern growth of the new energy industry to provide the most significant potential for industrial growth and economic performance. Specifically, the influence of digital transformation on the new energy industry is evaluated from the total factor productivity perspective using firm-level data. The first marginal contribution is that we explore the role of digital transformation in improving new energy enterprises' total factor productivity. Existing studies have investigated the promotion factors of enterprise total factor productivity, such as R&D investment [22], capital subsidies [23], resource allocation efficiency [24], market-oriented reforms [25] and green credit policies [26]. The improvement of total factor productivity in the new energy industryis faced with many technical difficulties, such as the weak foundation of enterprise production informatization, the apparent lag of digital research and application in the new energy field, and the insufficient integration of digital technology withthe new energy industry, seriously hindering the development of the new energy industry in the short term. This is the first research to systematically examine the influence of digital transformation on new energy enterprises' total factor productivity using firm-level data. We find that digital transformation enables new energy enterprises to achieve higher total factor productivity.

Second, this paper explores the heterogeneous effects of digital transformation on enterprises' total factor productivity in terms of ownership types and locations. The disparities in operation characteristics between state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs), as well as the regional heterogeneity in China, have significant effects on enterprise performance and total factor productivity [27–30]. Hence, this paper fills a gap in the literature by exploring the heterogeneous impact of digital transformation on new energy enterprises' total factor productivity. Our empirical conclusions reveal that the significant promotion impact of digital transformation occurs only in SOEs and the eastern area.

Third, in this paper, from the perspective of operation efficiency, operation costs and innovation power, we endeavor to assess the mechanisms of digital transformation on a firm's total factor productivity from a more systematic perspective. Previous research on digital transformation is inclined to examine its direct impact on enterprise performance [4], lacking a deeper understanding of the indirect mechanisms of digital transformation affecting firm-level total factor productivity. The findings in this paper show that better efficiency, lower cost and excellent innovation are the three mediating factors for the promotional effects of digital transformation on a new energy firm's total factor productivity. Hence, this study adds to the existing research on successful digital transformation strategies.

The remaining sections of this paper are arranged as follows: Section 2 documents the literature review and hypotheses, and Section 3 presents the methods and data. Further, Section 4 reports and discusses the empirical findings, and Section 5 summarizes the paper and outlines corresponding policy implications.

2. Literature Review and Theoretical Hypothesis

2.1. Literature Review

Existing research has richly addressed the definition of digital transformation, but has not yet formed a unified and clear view [31]. These definitions emphasize critical aspects of digital transformation. Specifically, Frank et al. [32] defined digital transformation as applications of digital technology to optimize the entire business process, such as improving customer experience, simplifying operational processes and creating new business models, thus improving enterprises' performance and market competitiveness. Agarwal et al. [33] described the digital transformation as the use and quantification of information technology. Fitzgerald et al. [34] stated that digital transformation is applying cutting-edge digital tools to achieve business gains. Coincidentally, Piccinini et al. [35] and Majchrzak et al. [36] defined digital transformation similarly to Fitzgerald et al. [34]. Matt et al. [37] and Tabrizi et al. [38] indicated that the core of digital transformation was strategic change. In a word, digital transformation can be summarized as "enterprise + technology + data", the advantages of which are value creation and mode innovation. In terms of digital transformation indicators, some scholars use single indicators such as the scale of hardware equipment size and a structured scale, which is not in line with the characteristics of digital transformation [39]. How to boost digital transformation has also attracted the attention of some scholars, who believe that management teams' internal strength and enterprises' dynamic capabilities are important driving forces for digital transformation [40]. In addition, previous research has deeply explored in depth the impact of digital transformation on enterprises' development, such as through the changing production mode, organization mode, and business model [41,42]. This paper focuses on the effects of digital transformationon a firm's total factor productivity.

2.2. Theoretical Hypotheses

This study attempts to certify that digital transformation can significantly foster total factor productivity, suggesting that a unit rise in digital transformation will result in a higher level of total factor productivity. Enterprise total factor productivity describes a combination of labor productivity and capital productivity, which is not only the core indicator to measure enterprise performance, but also one of the key indicators to measure high-quality economic development [43]. The majority of research has confirmed the promotion role of digital transformation in enterprise performance [44–47]. In particular, by updating its existing processes, a firm can flexibly achieve competitive advantages and considerable economic performance from the standpoint of dynamic capability [48]. However, some studies have put forth the view that digital transformation can directly hamper enterprise performance. Buttice et al. [49] believed that if there was fraud in digital technology, the economic benefits of enterprises would be significantly reduced. Shah et al. [50] proved that enterprise digital transformation tended to cause a market monopoly and reduces the market competitiveness of enterprises. In addition, Curran [51] concluded that traditional digitalization had no significant influence on enterprise performance.

In the early days, digital transformation for enterprises focused on building hardware platforms and devices and slowly expanded into reorganizing corporate strategies, organizational structures, business models, customer experiences and even business philosophies [52]. Compared with established concepts such as IT adoption, digital transformation is more continuous and comprehensive, with characteristics such as convergence, leapfrogging and strong environmental dependencies [53]. Further, the role of digital transformation on enterprise total factor productivity can be summarized into three aspects. First, digital transformation can enhance intrafirm communication [54]. Through digital transformation, we can enhance the communication between management and shareholders, and management and employees. In addition, digital technology is characterized by openness, interactivity and sharing. With the further penetration of digital technology in firms' operations, the goal and direction of digital transformation gradually lead to reducing the information asymmetry between supply and demand, thus saving costs for a firm. Second, digital transformation can assist a company in expanding a new network and enhancing worldwide competitiveness. Essentially, digital transformation can reduce the organization's obstacles [55]. Hence, a company promotes its access to new forms of information and connection, resulting in more resources for innovation and market internationalization [56]. Moreover, different enterprises will be tightly integrated in terms of resources, technologies, products and customers, creating a trend of continuous learning and dynamic cooperation among enterprises that will optimize and reconstruct the innovation process [57]. Third, a firm's strategic decisions will affect the effective implementation of digital transformation [58]. If a firm's strategy chooses digital transformation, it shows that it intends to increase enterprise value by adopting cutting-edge digital technologies [59]. Specifically, digital transformation can help enterprises respond quickly to market demand and enhance industrial specialization and collaborative operation, thereby improving the overall enterprise operation efficiency [45]. In summary, the application of digital transformation improves a firm's costsavings, innovation and operation efficiency. Therefore, a firm undergoing digital transformation may mean better performance. Just as enterprise performance in other fields, the enterprise total factor productivity in the new energy industry may also be stimulated by digital transformation. Accordingly, wepropose the first hypothesis:

Hypothesis 1: *Digital transformation can drive new energy enterprises' total factor productivity.*

The relative impact of the barriers or drivers to an enterprise's development may vary depending on the enterprise-related structural characteristics such as ownership and the level of regional growth [28]. There are three alternative ownership theories, including the social, political and agency theories [29]. According to the social perspective, in addition to preserving the value of state-owned assets, SOEs often assume more social duties, such as quickly addressing market failures and raising the overall social welfare. The political view claims that politicians use SOEs to achieve personal benefits. Like the social view, the agency view contends that SOEs are established for social advantages; nevertheless, it recognizes the possibility of corruption and misallocation caused by SOEs. Moreover, government ownership affects a firm's access to external resources and information, as well as its response to laws [60]. In China, both SOEs and NSOEs contribute significantly to the growth of the economy [30]. The differences between SOEs and NSOEs lie mainly in access to resources, distribution and the acquisition of government subsidies [61]. SOEs have a tighter political connection than NSOEs and can achieve financial support and other resources more efficiently. Meanwhile, SOEs face less competitive market pressure because of state credibility support, and they are likely to fully exploit the advantages of digital transformation and accelerate the integration of digital innovation with the production process. Conversely, NSOEs have more severe resource constraints and are often at a relatively weak position in the industrial chain. Especially when they invest more resources in digital transformation projects, other projects that can improve production efficiency will be eliminated in the face of fierce market competition pressures, leading to a slow digitalization process and low productivity [62]. The uneven development of China's regions is another critical aspect of the country. Some scholars have argued that regional factors play a vital role in total factor productivity [27–30]. Regional factors primarily include economic level, technical progress, industrial structure, and government subsidy intensity [28]. The divergences in the factor and product markets result in varying levels of digital transformation, which further exacerbates the disparity in total factor productivity driven by digital transformation [9]. Expressly, in terms of factor endowments, infrastructural development and the industrial development environment, it is generally accepted that in China, the eastern region is more advanced than the central and western areas [63]. In addition, both the availability of digital technologies for firms and the role of digital transformation vary across regions [9]. We base the following assumptions on the preceding discussion:

Hypothesis 2: *The impact of digital transformation on total factor productivity varies with the firm's ownership.*

Hypothesis 3: *The impact of digital transformation on total factor productivity varies with the firm's location.*

The characteristics and nature of the aforementioned digital transformation also determine the mechanism by which it functions, that is, by increasing operation efficiency, cutting costs and enhancing innovation to enhance enterprise total factor productivity. The first is to improve operation efficiency and management level. Operating efficiency consists of two main aspects [64,65]. Internally, new energy enterprises extensively employ digital information technologies in all aspects of the operations to enhance production efficiency, organizationand docking. From an external perspective, the acquisition of external business information by new energy enterprises may be made more efficient and rapid. Whether it is market data or informationfeedback from stakeholders, it is less difficult to convey corporate information to the outside world, thus considerably enhancing a firm's operation efficiency.

The second is to decrease costs and enhance enterprises' market competitiveness. New energy enterprises are increasingly turning to digital technologies to improve communication channels and accelerate the sharing of business data, which can streamline communication across different departments and avoid needless delays in enterprise decision-making, thus decreasing enterprises' operation costs. Meanwhile, digital transformation can strengthen production management, improve resource utilization efficiency and promote cost control [10,42]. Therefore, new energy enterprises can use digital transformation to reduce costs and increase their market competitiveness.

The third is to create an excellent innovation environment and enhance innovation power. Digital transformation can provide sufficient power sources and technological needs for technological innovation, which is conducive to creating an ideal ecological environment for innovation in the production and operation of new energy enterprises, and promoting the organizational structure and configuration of technological elements of firms to obtain a form beneficial to technological innovation [66]. In order to proactively fit this market orientation, new energy enterprises often have a stronger incentive to invest more in research and development to differentiate their products through technological innovation, meeting the consumers' individual needs and improving core product competitiveness. In addition, new energy enterprises' digital transformation can significantly improve the utilization efficiency of innovation resources [67]. Unlike closed innovation, a new generation of information technology is used by new energy enterprises to actively absorb external knowledge, forming an open innovation model that integrates internal and external innovation resources, significantly improving the enterprises' innovation efficiency.

Hypothesis 4: *Digital transformation can indirectly promote new energy enterprises' total factor productivity by increasing operation efficiency, cutting costs and enhancing innovation.*

3. Methodology and Data

3.1. Empirical Model

3.1.1. Baseline Model

This study builds a benchmark model to capture the relationship between digital transformation and new energy enterprises'total factor productivity. The specification we estimated is as follows:

$$TFP_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where TFP_{it} is total factor productivity. DT_{it} is digital transformation. $Controls_{it}$ is a set of variables that control the impact of other factors on total factor productivity. μ_i is the individual fixed effect, λ_t is the time fixed effect and ε_{it} is the error term.

3.1.2. Mediation Effect Model

The above empirical analysis only examines the core relationship between digital transformation and total factor productivity in new energy companies and has not yet explored the black box of mechanisms involved. The theoretical analysis above suggests that technological innovation and internal control play a vital role as mediating variables between digital transformation and enterprise total factor productivity. To further clarify how digital transformation affects new energy enterprises' total factor productivity, this research uses the successive test in Baron and Kenny [68] to investigate Equation (1) and two different equations below:

$$Med_{it} = \theta_0 + \theta_1 DT_{it} + \theta_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$TFP_{it} = \phi_0 + \phi_1 Med_{it} + \phi_2 DT_{it} + \phi_3 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where Med_{it} represents the mediation variables. If a mediating variable acts as a mediating variable between digital transformation and total factor productivity, we anticipate both θ_1 and ϕ_1 to be significant.

3.2. Explanation of the Variables

3.2.1. Measurement of Total Factor Productivity

The explained variable in this paper is total factor productivity (TFP). The LP method employs intermediate inputs as the instrumental variable for evaluatingtotal factor productivity at the firm level, thus avoidingthe issue of simultaneity bias generated by the simultaneous selection of production and capital stock by enterprises. Therefore, this study uses the LP method to measure a new energy firm's total factor productivity. Referring to relevant studies on the LP method [69,70], we take the number of employees and net fixed assets of companies as labor and capital input variables, respectively, and select the companies' operating income as the output variable. Meanwhile, the sum of all expenses, excluding depreciation and amortization, is used as the intermediate input variable.

3.2.2. Measuring Digital Transformation

The core explanatory variable in this research is DT. The existing research on enterprise digital transformation mainly stagnates with regard to qualitative analyses, and there is a lack of quantitative analyses [71]. Therefore, we apply Python software to conduct textual recognition on the annual reports of new energy companies [57]. The words and expressions used in the annual reports represent critical strategic orientations for the development of new energy companies, reflecting their concern for business orientation and future development clues.

The steps to obtain a firm's digital transformation information are as follows: First, we conduct textual analysis on the annual reports of new energy enterprises using Python software, which can identify the keywords related to digital transformation (see Table 1). Second, after identifying annual reports with the keywords, we use Python to crawl all the text in the annual reports of listed new energy enterprises and match them with the keywords. Finally, the number of occurrences of each keyword is counted and summed up to create the total number of occurrences in every annual report. In addition, we denote DT as the natural logarithm of 1 plus the total number of occurrences.

Table 1. Keyword classification for the digital transformation of new energy companies.

Dimension	Category	Keywords
Underlying technology	Artificial intelligence	business intelligence; artificial intelligence; investment decision aid; intelligent data analysis; image understanding; intelligent robot; deep learning; semantic search; machine learning; biometric; face recognition; voice recognition; identity verification; natural language processing
	Cloud computing	cloud computing; graph computing; stream computing; in-memory computing; brain-like computing; cognitive computing; multi-party; secure computing; green computing; billion-level concurrency; EB-class storage; converged architecture; Internet of Thing; information physical system; supercomputer; computational science; cloud platform; edge computing
	Big data	text mining; data visualization; data mining; credit augmented reality; heterogeneous data; mixed reality; virtual reality; big data; imaging; ICT
	Blockchain	blockchain; distributed computing; differential privacy technology; digital currency; intelligent financial contract
Practical application	Industry-specific application	new energy digitalization; intelligent new energy; intelligent new energy service; new energy intelligent system; intelligent new energy management; digital new energy; new energy digital system; intelligent new energy; digital new energy product; intelligent emergency; intelligent operation and maintenance; digital interconnection; digital ecology; digital process; digital business; interactive grid; digital grid; grid digitalization; intelligent hydropower; hydropower digitalization; intelligent battery; intelligent wind power; digital wind power; digital offshore wind power; new energy information; digital wind farm; intelligent microgrid; intelligent photovoltaic; digital photovoltaic; photovoltaic cloud platform; intelligent hydrogen; intelligent light energy; intelligent solar energy; virtual power plant; intelligent oil and gas pipeline; intelligent nuclear power; intelligent power plant; intelligent power equipment; digital empowerment; digital new energy industry; digital new energy monitoring; digital new energy management; intelligent newenergy infrastructure

3.2.3. Mediation Variables

In the hypothesis creation, we have stated that digital transformation is not just the digitization of data, but the improvement of productivity and product quality by using a range of sophisticated digital technologies and a variety of hardware systems. Moreover, digital transformationcan increase operation management, cut costs and enhance innovation to improve enterprise total factor productivity, which is reflected in better asset turnover (AT), lower operating costs (OCs) and stronger innovation power (IP), respectively. Therefore, this research contends that AT, OC and IP are three transmission mechanisms for the effects of digital transformation on a new energy enterprise's total factor productivity. Specifically, AT is measured by the ratio of a company's total revenue to total assets. OC is represented by the ratio of total production cost to total revenue. The natural logarithm of 1 plus the total number of patents held measures IP.

3.2.4. Control Variables

The control variables used for this research include company size (CS), return on total assets (ROA), revenue growth rate (RGR), asset liquidity (AL) and equity concentration (EC). Company scale is measured as the natural logarithm of year-end total assets. Return on total assets is represented by the ratio of an enterprise's net profits to total assets. Asset liquidityis measured by current assets divided by current liabilities. Equity concentration is calculated by the percentage of shares owned by the largest shareholder.

3.3. Data sources and Processing

According to the categorization criteria of the Industry Classification Guidelines for Listed Companies (revised in 2012), this research selects all A-share listed new energy enterprises in China for 2009–2021. The beginning of the date range, 2009, is intended to prevent the influence of the 2008 worldwide financial crisis that may affect a company's total factor productivity or its strategy for digital transformation. In order to guarantee the accuracy and validity of the empirical findings, the criteria for selection are: (1) ST-(special treatment, i.e., enterprises that have suffered operating losses for two consecutive years) and *ST-(enterprises' operation losses for three consecutive years) listed enterprises are excluded; and (2) enterprises with missing data are deleted. To prevent extreme values from skewing the findings, we winsorize all variables at the 1% and 99% levels. The financial data are obtained from the database of CSMAR, and the final sample has a total of 152 new energy enterprises.

As shown in Table 2, the findings of descriptive statistics suggest that the generalvariance of the data is small, and there is no extreme-value issue. Table 3 provides correlation test results. The correlation coefficient between TFP and DT is 0.1437, and the absolute values of the correlation coefficients of the other variables almost do not exceed 0.5, suggesting that the regression results are not subject to multicollinearity problems.

Table 2. Descriptive statistics of variables.

Variables	Obs	Mean	Std. Dev.	Min	Max
TFP	1976	7.0179	1.2225	4.2314	10.6423
DT	1976	1.6935	1.2947	0.0000	4.2195
AT	1976	0.5233	0.2586	0.1243	0.7491
OC	1976	0.3562	0.2169	0.0950	0.6317
IP	1976	0.5961	0.9453	0.0000	6.0753
CS	1976	21.7452	1.2875	19.0532	26.1975
ROA	1976	0.0310	0.0407	−0.0260	0.1504
RGR	1976	0.1387	0.2461	−0.5597	2.2481
AL	1976	0.5098	0.1415	0.1411	0.7185
EC	1976	22.7315	5.5253	7.6283	67.1237

Table 3. Correlation coefficients.

Variables	TFP	DT	AT	OC	IP	CS	ROA	RGR	AL	EC
TFP	1.0000									
DT	0.1437 ***	1.0000								
AT	0.0404 ***	0.0207	1.0000							
OC	−0.0265 ***	−0.0492 ***	−0.0311	1.0000						
IP	0.0463 ***	0.0641 ***	0.0510 ***	0.0253 **	1.0000					
CS	0.1402 ***	0.0109 ***	0.0743 ***	0.0218 **	0.0276	1.0000				
ROA	0.1233 ***	0.1033 ***	0.1231 ***	0.1048 ***	0.0544 ***	0.4096 ***	1.0000			
RGR	0.3018 ***	−0.0207	0.0315 **	0.1263 ***	0.0251	0.0242	0.2204 ***	1.0000		
AL	−0.0407 ***	0.0189 ***	0.0446 ***	0.0538 ***	0.0848 ***	−0.1426 ***	−0.0364	0.2100 ***	1.0000	
EC	0.1248 *	0.0040	0.0731 ***	0.0352 **	0.0663 ***	−0.2960 ***	0.1645 ***	0.0143 **	0.1286 ***	1.0000

Note: ***, ** and * mean that the levels of significance are 1%, 5% and 10%, respectively.

4. Empirical Results and Discussion

4.1. Baseline Results

We examine the impact of digital transformation on new energy enterprises' total factor productivity using model (1). The findings are shown in Table 4. In column (1), when only individual and time fixed effects are controlled, the coefficient of digital transformation is positive and significant at 1%, indicating that digital transformation has a positive impact on a new energy firm's total factor productivity. From the findings in column (2), which includes all the control variables, we infer that a unit increase in digital transformation increases the enterprise total factor productivity by 0.0212 percentage points. Hence, whether or not the control variables are included, the findings indicate that the higher a new energy firm's digital transformation level, the higher its total factor productivity, suggesting Hypothesis 1.

Table 4. Baseline results.

Variables	TFP	TFP
	(1)	(2)
DT	0.0495 *** (4.27)	0.0412 *** (4.48)
CS		0.2683 *** (7.34)
ROA		1.5936 *** (6.35)
RGR		0.0214 *** (4.73)
AL		0.5189 *** (7.34)
EC		−0.0025 (−1.28)
Constant	5.4175 *** (12.63)	−2.5931 *** (-8.74)
IE	YES	YES
YE	YES	YES
Observations	1976	1976
R-squared	0.3154	0.5376

Note: The t-statistics are reported in the parentheses. *** means that the level of significance is 1%.

In column (2), the impact coefficients of all control variables are positive and significant except equity concentration, which demonstrates that new energy enterprises with a large scale, growing profitability and high asset liquidity generally possess a higher total factor productivity. One probable reason for this result is that large-scale new energy enterprises often have standardized production and management systems in place, allowing them to promote output efficiency, even in a complex and changing environment. Similarly, enterprises with high profitability can widely absorb and use social investment funds, boosting the growth and turnover of total capital and increasing their productivity. Furthermore, it is easier for a firm to turn assets into cash if they have a higher asset liquidity, which helps the firm cope with external uncertainties and improve performance [72].

4.2. Robustness Check and Endogenous Discussion

4.2.1. Robustness Test

Eliminating Specific Samples

To assess the reliability of the benchmark model's outputs, we conduct a variety of robustness tests. Shocks from major adverse financial events will hinder the digital transformation process of enterprises. In recent years, there has been a relatively significant financial shock at home, that is, the China stock market crash in 2015. Thus, the sample data for 2009–2014 and 2016–2021 are retained in the regression analysis for robustness. Moreover, considering the ongoing severe shock of the COVID-19 pandemic on various sectors, we further omit the sample data for 2020 and 2021 based on the previous treatment.The results of columns (1) and (2) in Table 5 prove that eliminating specific samples will not change the positive relationship between digital transformation and a new energy firm's total factor productivity, which verifies the fundamental conclusion's validity.

Table 5. Robust test: eliminating specific samples.

Variables	Excluding the Sample Data for 2015	Excluding the Sample Data for 2015, 2020 and 2021
	TFP	TFP
	(1)	(2)
DT	0.0371 ***	0.0325 ***
	(4.10)	(3.47)
Controls	YES	YES
Constant	−3.1294 ***	−2.5786 ***
	(−11.56)	(−8.23)
IE	YES	YES
YE	YES	YES
Observations	1824	1520
R-squared	0.4946	0.4558

Note: The t-statistics are reported in the parentheses. *** means that the level of significance is 1%.

Extending Observation Window

To avoid the impacts of the time observation window, DT is treated with a lag of one to three periods and TFP is treated with a lead of one to three periods in this research. Based on the estimation results of columns (1) to (6) in Table 6, whether DT is lagged or TFP is front-loaded, there is still a significant positive relationship betweendigital transformation and total factor productivity innew energy enterprises.This contribution does not diminish significantly with the extension of the time observation window, which again verifies that the core conclusion is reliable in this paper.

Adjustment of Variables

Financial leverage has a direct impact on a firm's profitability and company age can affect its dynamism and innovation, both of whichcan produce a vital influence on a firm's total factor productivity. Hence, the two variables should be added to the estimation of the benchmark model to address endogeneity problems. Specifically, financial leverage is calculated by the ratio of total liabilities to total assets. According to columns (1) and (2) in Table 7, the digital transformation of new energy enterprises still significantly drives their total factor productivity, which is consistent with the baseline model's findings. In addition, we recalculate the digital transformation of energy companies by using the ratio of the portion of intangible assets related to digital transformation in listed companies' annual reports to intangible assets.

Table 6. Robust test: extending observation window.

Variables	TFP	TFP	TFP	F1.TFP	F2.TFP	F3.TFP
	(1)	(2)	(3)	(4)	(5)	(6)
DT				0.0326 *** (4.58)	0.0302 *** (4.13)	0.0297 *** (3.86)
L1.DT	0.0345 *** (4.64)					
L2.DT		0.0316 *** (4.27)				
L3.DT			0.0284 *** (3.57)			
Controls	YES	YES	YES	YES	YES	YES
Constant	−2.6432 *** (−8.46)	−2.7604 *** (−9.20)	−2.7285 *** (−8.69)	−3.0756 *** (−9.32)	−2.7003 *** (−7.85)	−3.1641 *** (−10.25)
IE	YES	YES	YES	YES	YES	YES
YE	YES	YES	YES	YES	YES	YES
Observations	1824	1672	1520	1824	1672	1520
R-squared	0.4624	0.4510	0.4165	0.4428	0.4375	0.4306

Note: The t-statistics are reported in the parentheses. *** means that the level of significance is 1%.

Table 7. Robust test: adjustment of variables.

Variables	Adding Control Variables TFP	Changing Core Explanatory Variable TFP
	(1)	(2)
DT	0.0465 *** (4.97)	0.0412 *** (4.13)
Controls	YES	YES
Constant	−1.3570 *** (−6.41)	−2.6631 *** (−9.52)
IE	YES	YES
YE	YES	YES
Observations	1976	1976
R-squared	0.5662	0.5175

Note: The t-statistics are reported in the parentheses. *** means that the level of significance is 1%.

On the whole, the results obtained by excluding specific samples, extending the observation window, adding control variables and changing the core explanatory variable show that the proposed model has excellent explanatory power and robustness for examining the impact of digital transformation on a new energy firm's total factor productivity. Hypothesis 1 is again supported.

4.2.2. Endogenous Discussion

In the empirical study of this paper, there may be endogeneity problems caused by reverse causality. In other words, new energy enterprises with high productivity are more inclined to carry out digital transformation, and increases in total factor productivity may be the cause rather than the result of digital transformation. Therefore, the endogeneity problems are more effectively resolved by employing appropriate instrumental variables in this study. Specifically, the digital development level of the other new energy companies in the same region affects the digital transformation decisions of this new energy company. However, it does not directly affect the total factor productivity of this new energy company. Under the circumstances, the instrumental variable generated can meet the correlation and exogeneity. Therefore, in this research, the mean value of the digital transformation level of all new energy enterprises in the same province except for this new energy company is selected as the instrumental variable. In addition, by referring to the relevant research [73,74], we create the interaction term (HDel) as another instrumental variable using the number of post and telecommunications bureaus per million in 1984 and China's internet users in the previous year. The two-stage least squares method (2SLS) is used for the estimation. The results of columns (1) and (2) in Table 8 indicate that a new energy company can boost its total factor productivity by embracing digital transformation. The Kleibergen–Paap rk LM statistic and the Kleibergen–Paap rk Wald F-statisticreject the null hypothesis, indicating that it has passed the endogenous test. The aforementioned regression results further demonstrate that digital transformation makes a positive impact on firms' total factor productivity.

Table 8. Endogenous test.

Variables	TFP	TFP
	(1)	(2)
DT	0.0314 *** (3.43)	0.0504 *** (4.15)
Controls	YES	YES
Constant	−2.9581 *** (−9.24)	−2.3426 *** (−7.02)
IE	YES	YES
YE	YES	YES
Kleibergen–Paap rk LM statistic	436.742 [0.0000]	493.623 [0.0000]
Kleibergen–Paap rk Wald F statistic	274.850 {62.76}	319.539 {74.25}
Observations	1976	1976
R-squared	0.4125	0.5831

Note: *p*-value in square brackets; the critical value at the 10% level of weak identification test in braces. The t-statistics are reported in the parentheses. *** means that the level of significance is 1%.

4.3. Heterogeneity Analysis

4.3.1. Ownership Heterogeneity

To compare the impact of digital transformation under different enterprise ownerships, we divide the whole sample into two subsamples: SOEs and NSOEs. In column (1) of Table 9, consistent with the baseline findings, the regression coefficient of digital transformation is significantly positive, indicating that digital transformation drives the total factor productivity of SOEs. Conversely, in column (2), the same impact coefficient has no significant impact on total factor productivity in NSOEs. Our findings support the view that compared with NSOEs, SOEs are more likely to promote their total factor productivity through digital transformation. The theoretical hypothesis H2 is supported. As explained in Section 2.2, SOEs have the potential to receive additional government funding and attract more external investment possibilities, thus having more advantages in driving enterprise digital transformation. Nevertheless, NSOEs are under pressure to achieve economic benefits and contend with increasing market competition. Thus, maintaining their daily operations has become the main task at this stage. In this context, the investment efficiency of NSOEs is declining, which seriously impedes the advancement of digital transformation.

4.3.2. Regional Heterogeneity

To examine the regional heterogeneity of digital transformation affecting a new energy firm's total factor productivity, this research divides the whole sample into three subsamples based on the firms' location: the eastern, the central and the western region. The subsample regression results in columns (3)–(5) of Table 9 show that the significant promoting effect of digital transformation occurs only in the eastern region. Unfortunately, the promoting effect in the central and western regions is insignificant. The theoretical hypothesis H3 is verified. In fact, enterprises in the eastern region not only have more financial subsidies from local governments, but also face fiercer competition. This competition, in turn, increases the incentive to undertake digital transformation. The above analysis further confirms the role of digital transformation leaders in the east. Conversely, government support and fiercer competition may be inefficient in promoting firms' digital transformation in the central and western areas.

Table 9. Heterogeneity test.

Variables	SOEs TFP	NSOEs TFP	Eastern Region TFP	Central Region TFP	Western Region TFP
	(1)	(2)	(3)	(4)	(5)
DT	0.0593 ***	−0.0121	0.0713 ***	0.0214	0.0116
	(5.18)	(−1.53)	(6.24)	(1.55)	(1.23)
Controls	YES	YES	YES	YES	YES
Constant	−2.6324 ***	−0.2563 ***	−2.1245 ***	−1.4543 ***	−1.154 ***
	(−5.32)	(−3.54)	(−7.81)	(−4.48)	(−3.89)
IE	YES	YES	YES	YES	YES
YE	YES	YES	YES	YES	YES
Observations	637	1339	1261	546	169
R-squared	0.5485	0.2904	0.6620	0.2575	0.2361

Note: The t-statistics are reported in the parentheses. *** means that the levels of significance are 1%.

4.4. Identification Test of Indirect Effect Mechanism

A further problem from the above results is the transmission mechanism, through which digital transformation affects new energy enterprises'total factor productivity. This section analyzes the mediation effects of digital transformation on total factor productivity from three perspectives: operation efficiency, operating costs and innovation power. The results are shown in Table 10.

Table 10. Mediating effects.

Variables	AT	TFP	OC	TFP	IP	TFP
	(1)	(2)	(3)	(4)	(5)	(6)
DT	0.0411 ***	0.0384 ***	−0.1112 ***	0.0317 ***	0.0458 ***	0.0385 ***
	(4.32)	(4.42)	(−3.75)	(3.75)	(5.53)	(3.85)
AT		0.0681 ***				
		(5.70)				
OC				−0.0854 ***		
				(−3.57)		
IP						0.0764 ***
						(4.12)
Controls	YES	YES	YES	YES	YES	YES
Constant	−2.3915 ***	−2.1861 ***	1.2350 ***	−2.5401 ***	−2.9254 ***	−2.0356 ***
	(−6.63)	(−5.37)	(4.72)	(−6.28)	(−7.32)	(−5.58)
IE	YES	YES	YES	YES	YES	YES
YE	YES	YES	YES	YES	YES	YES
Observations	1976	1976	1976	1976	1976	1976
R-squared	0.4742	0.5123	0.3274	0.4742	0.3625	0.4574

Note: The t-statistics are reported in the parentheses. *** means that the levels of significance are 1%.

In columns (1), (3) and (5), the coefficients of digital transformation are all significant and exhibit the expected signs. Specifically, the coefficient of digital transformation is significantly negative in column (3), suggesting that digital transformation can reduce a firm's operating costs. The same coefficients are positive and significant in columns (1) and (5), indicating that digital transformation can promote operating efficiency and innovation power. Then, in columns (2), (4) and (6), the coefficients of AT, OC and IP are all significant with the corrected signs, whereas the coefficients of digital transformation carry the expected signs. Therefore, digital transformation can reduce operating costs, and improve operating efficiency and innovation power, thus promoting total factor productivity. The theoretical hypothesis H4 is supported. In fact, accelerating the digital transformation process aligns with the requirements of national policies and economic practices for firms, helping to improve their productivity and reduce management friction in various operational processes. Especially in the growth phase of a firm, digital technology used to develop and mine data in depth can make the value of data be better reflected in its operation. Hence, new energy companies can use digital transformation to deepen their primary business and expand across industries, all of which will undoubtedly benefit their operation efficiency. Moreover, digital transformation will increase the innovativeness and profitability of enterprises and provide a stable basis for reducing their operating costs. In addition, digital transformation may give adequate assistance for firms to effectively allocate innovative resources, thus promoting firms' innovation output. As a result, firms with higher operation efficiency, cost reduction and innovation enhancement will have higher total factor productivity.

5. Conclusions and Policy Implications

Faced with the wave of rapid technological innovation, new energy enterprises must accelerate the pace of digital transformation. Due to the potential influence of digital transformation on new energy enterprises' production, management and profitability, this paper selects China's new energy enterprises as research objects to investigate the effects of digital transformation on total factor productivity. Based on a sample of Chinese A-share listed new energy enterprises from 2009 to 2021, we discover that digital transformation can enhance a new energy firm's total factor productivity. This finding is robust when some specific samples are eliminated, the observation window is extended, new control variables are included and the core explanatory variable is changed. Specifically, the promoting effect of digital transformation on total factor productivity is significant in SOEs rather than NSOEs. Meanwhile, digital transformation has a significant positive impact in the eastern areas, but not in the central and western areas. Moreover, we argue that the impact of digital transformation on total factor productivity is transmitted via cost reduction, the enhancement of operating efficiency and innovation strength. In addition, this article helps us to understand the total factor productivity level of new energy enterprises in China, and explore the improvement path of total factor productivity in China's new energy enterprises from the perspective of digital transformation, which expands the horizon and depth of new energy enterprise performance research and digital transformation research.

From the perspective of policy, this research offers crucial implications for optimizing the role of digital transformation. On the one hand, it is helpful for local governments to promote digital transformation policies, such as providing a platform for enterprises to adopt a digital transformation strategy. Similar to the expenses and challenges associated with corporation innovation, digital transformation adoption may be a lengthy and challenging process. We hold that digital transformation adoption can promote operating efficiency and innovation power, which is crucial to a firm's success and a nation's economic growth in the digital age. Additionally, the adoption process of digital transformation is slow-moving. Even though there are clear advantages to digital transformation for a firm, such as improving operation efficiency and saving costs, many companies still confront various obstacles when starting the adoption. Hence, a government should offer a favorable legislative environment for enterprises to embrace digital transformation, thus reducing the cost of digital transformation and shortening the learning curve. On the other hand, the heterogeneous effects of digital transformation should be emphasized. The local government's public policy should be modified according to the firms' ownership, geographical location and sensitivity to various policies. For instance, government support, such as financial subsidies, should be designedly increased in NSOEs and firms in the central and western areas. It is worth mentioning that the acquisition and use of financial subsidies should be more strictly monitored to effectively provide financial support for new energy enterprises' digital transformation.

This research presents a preliminary discussion about the role of digital transformation in the total factor productivity of new energy enterprises; however, there are potential limitations to this research. First, our database only covers China's A-share listed enterprises because of data unavailability. Domestic unlisted and non-A-share market firms that produce and sell domestically are not examined. Second, we use the strategy of integrating theoretical hypotheses with empirical testing to perform the appropriate study, which can be approached from various angles. Subsequent studies may attempt to establish a theoretical model that explains the motivating influence of digital transformation on a new energy firm's total factor productivity. Finally, to further promote generalization of the results, it might be more meaningful to investigate the effects of digital transformation on new energy enterprises' total factor productivity in other emerging countries.

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