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The Impact of Digital Transformation on Corporate Sustainability: Evidence from Listed Companies in China

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Abstract: This study investigated whether digital transformation improves corporate sustainability. In particular, we focused on the mediating effects of operation efficiency and corporate innovation in the ability of digital transformation to enhance corporate sustainability. A novel analytical framework was constructed incorporating the resource-based view (RBV), institution-based view (IBV), enterprise efficiency theory and dynamic capability theory to explain the relationship between digital transformation and corporate sustainability. Fixed effects estimation and the 2SLS method were used to test our analytical framework based on Chinese A-share listed companies over the sample period, 2014–2020. We found that digital transformation is an important means to improve corporate sustainability, but this relationship is impacted by the heterogeneous factors of ownership, industry and location. At the end of the paper, implications, limitations and future research directions are discussed.

Keywords: digital transformation; sustainability; mediating effects; operation efficiency; corporate innovation

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1. Introduction

With the rapid progress of information technology, digital technology, represented by big data, artificial intelligence and cloud computing, has been leading society and the economy into the digital era. According to a white paper on the development of China's digital economy (2021) released by the China Academy of Information and Communication, the added value of China's digital economy accounted for 38.6% of GDP in 2020, and its growth rate reached 3.2 times the GDP growth rate. Digital resources are becoming the core production factors driving the flow of technology, capital, talent and materials [1]. Developing a digital economy has become a common choice for governments aiming to reshape regional competitiveness [2]. UN Sustainable Development Goal 9 puts forward the goals of developing a resilient infrastructure, improving technological capabilities, increasing Internet access to the least-developed countries and promoting the integration of small-scale industries and enterprises into global value chains [3]. The African Union's "Digital Transformation Strategy for Africa 2020–2030" believes that digital transformation is a driving force for innovation, inclusiveness and sustainable growth. South Africa has made digital transformation a key component of its National Development Plan for eliminating poverty and reducing inequalities by 2030 [4]. In China, the development of big data was also officially incorporated into national strategy in the Fifth Plenary Session of the 18th CPC Central Committee. The outline of the 14th Five-Year Plan (2021–2025) and the policy initiative Vision of 2035 further clarify the significance of promoting the deep integration of the Internet, big data, artificial intelligence and the real economy.

In recent years, the COVID-19 pandemic, trade wars and geopolitical conflict have led to a more complicated and tougher business environment. Continuously improving the sustainability of enterprises has become the winning strategy to address the turbulent external environment. In academia, scholars usually use sustainability or sustainable development to indicate the harmony between economic development and the ecological environment. In particular, corporate sustainable development is regarded as a multi-dimensional construct of social, economic and environmental development as well as a business strategy that seeks to satisfy the present demands without preventing future development [5,6], considering the issues around ecology and natural resources [7]. This branch of literature on sustainability is conducted more from the perspective of urban or regional development [8–10]. There is another branch of literature focusing on corporate sustainable management. For example, Baumgartner and Rauter (2017) integrated the strategic process, strategic content and strategic background to explore how corporate sustainable management contributes to create value for businesses, society and nature [6]. Johnson and Schaltegger (2016) discussed the reason for the implementation of sustainable management of SMEs and analyzed the obstacles and facilitating standards [11]. Klimek (2020) developed the basic principles of corporate sustainable capital management [7]. Although there are studies on the evaluation of sustainable development ability in enterprises [12–14] and sustainable management from the perspective of corporate capitals [15], there is a lack of further exploration into the important issue of how to improve enterprise sustainability, especially from the perspective of digital transformation. Corporate sustainability refers to continuous profitability and a competitive advantage in specific areas [16,17]. With the explosive growth and wide application of digital technology, data information has become a strategic resource for enterprises to enhance their core competitiveness and obtain potential opportunities [18]. However, to the best of our knowledge, less attention has been given to the impact and mechanism of digital transformation on corporate sustainability.

This study aims to fill the gap mentioned above and explore the impact of digital transformation on corporate sustainability as well as its internal mechanisms based on Chinese A-share listed companies during the period from 2014 to 2020. This study contributes to the literature in the following ways. First, this study takes digital transformation as a new perspective for explaining and understanding corporate sustainability. Previous studies mainly discussed this topic from the managerial perspectives of internal corporate governance mechanisms [13,19]. Furthermore, a novel analytical framework was constructed incorporating the resource-based view (RBV), institution-based view (IBV), enterprise efficiency theory and dynamic capability theory to explain the relationship between digital transformation and corporate sustainability. Second, this study explores the internal mechanism in this relationship represented by improving efficiency and promoting innovation, which helps understand the impact of digital transformation and enriches the research on corporate sustainability. Methodologically, this study tries to solve potential endogeneity issues with different instrumental variables. The findings of this study provide insights and implications for enterprise management and government decision-makers in pursuing sustainable development.

The structure of the rest of this paper is as follows. The second part reviews the literature and proposes research hypotheses. The third part is the research design, which introduces the data, variables and models. The fourth part is empirical research and analysis. The fifth part further discusses the mediating effects. The sixth part presents concluding remarks.

2. Literature Review and Hypothesis Development

2.1. Digital Transformation and Corporate Sustainability

Resources, capability and organization are the key factors that affect the operation efficiency of enterprises [20]. According to the strategic logic of the resource-based view, enterprises establish competitive advantages by accumulating valuable, scarce, nonimitative and irreplaceable resources [21]. With the rise of the digital economy, digital resources have become one of the most important factors in addition to land, capital and labor force. They can greatly improve productivity by empowering enterprises to realize intelligent production, operation and management, create more added value for enterprises and improve competitiveness [22–24]. Specifically, the deep integration of AI, cloud computing, blockchain technology and other technologies with traditional production factors promotes the optimization of business processes, the reduction of operating costs, the improvement of production efficiency and the establishment of an efficient and agile operating system and organizational management framework [25]. The smooth flow of internal information in the digital context helps alleviate the principal–agent problem; thus, it improves the internal control of enterprises and strengthens their resource allocation capability [26]. Digital transformation also helps enterprises break the original business management model and establish a new operating system and organizational management structure [27].

The institutional-based view (IBV) indicates that the growth of organizations depends on their ability to adapt to any changes in the external institutional environment, emphasizing the importance of external resources to the organization [28]. In the context of the continuous expansion of the industrial system and further specialization in the division of labor, digital transformation is no longer an isolated activity but a coordinated transformation among enterprises upstream and downstream in the industrial chain [29] as well as the process of continuous interaction with peer enterprises, digital platforms and government departments to obtain resources such as knowledge, technology and funds [30]. Therefore, digital transformation not only enables enterprises to master more digital resources, but also to connect more closely with other economic entities and obtain richer feedback. In addition, enterprises can make use of the information obtained to differentiate production and establish a competitive advantage. Mourtzis et al. (2014) find that with web-based platforms, enterprises can achieve a seamless connection between personalization and mass customization, realizing differentiation and cost minimization simultaneously [31]. The application of digital technology can accelerate the diffusion and dissemination of information to benefit the communication between enterprises and reduce search costs [32], which enables enterprises to reach a wider range of upstream and downstream companies and to compare themselves with potential competitors.

Therefore, the digital transformation of enterprises can optimize the allocation of internal and external resources as well as improve the efficiency of production, operation and management to enhance corporate sustainability. Based on the above analysis, we proposed the following hypothesis:

Hypothesis 1. *Digital transformation will improve corporate sustainability.*

2.2. The Heterogeneous Impact of Digital Transformation on Corporate Sustainability

Digital transformation is a long-term, tortuous and uncertain process [33]. It is widely confirmed that there are differences between state-owned enterprises and private enterprises in terms of risk preference, investment behavior, etc. [34,35]. For example, researchers find that nonstate-owned enterprises are more likely to focus on financial goals [36], whereas state-owned companies may pay more attention to social and political benefits [37]. Therefore, we argue that private enterprises may be more motivated to use digital transformation to reduce costs and promote innovation to enhance corporate sustainability. In addition, state-owned enterprises will also be favored by policy support, government subsidies, credit financing and other resources, facing less competitive pressure [38,39]. In a fiercely competitive environment, state-owned enterprises lack the intrinsic motivation to innovate, which blocks corporate sustainability. Conversely, most private enterprises are self-reliant and take more active advantage of digital transformation to consolidate their market position, improve their competitive advantage and obtain stronger innovative spirit and executive ability. Therefore, we proposed the following hypothesis:

Hypothesis 2a. *Compared with state-owned enterprises, private enterprises see more significant impacts from digital transformation improving corporate sustainability.*

The impact of digital transformation also shows industry heterogeneity [40]. Originating from the field of information and communication science, digital technology can deeply integrate with the underlying technology of the industrial production process so that digitization can be quickly applied to the manufacturing industry and improve the efficiency of procurement, production and sales [41,42]. For example, in industrial production workshops, enterprises can use various low-power sensors and Internet of Things communication to update the synchronous status of the production line and utilize big data analysis to control the running speed of equipment and the scheduling of workers to ensure efficient docking and close cooperation of many production links [41]. In the digital transformation of the tertiary industry and other industries, those enterprises should first discover the "pain points" in products and services, find matching digital technologies and finally develop terminal products with professional technicians. Therefore, compared with the manufacturing industry, other industries require longer effective wait times for digital transformation and more stringent conditions. At present, China's listed companies are still in the initial stage of digital transformation. Therefore, we proposed the following hypothesis:

Hypothesis 2b. *Compared with enterprises in the tertiary industry and other industries, the manufacturing industry sees more significant impacts on corporate sustainability from digital transformation.*

Considering the disparities in environmental advantages, policies and Internet development in different regions, there may also be differences in the digital transformation of enterprises. Compared with the central and western regions, the eastern region has a higher level of economic development, more complete information infrastructure and a more advanced technological level [43], providing enterprises with the conditions for more comprehensive and advanced digital transformation [44]; thus, the eastern region generally plays a leading role in the development of high-end digital industries. Therefore, enterprises in the eastern region are more likely to obtain opportunities for digital development and transformation as well as abundant high-quality digital talent, technical support and external resources, which support sustainable corporate development. Based on this, the following assumption was proposed:

Hypothesis 2c. *Compared with the central and western regions, the eastern region will see more significant impacts on corporate sustainability from digital transformation.*

2.3. The Mechanism of Digital Transformation Impacting Corporate Sustainability

According to the theory of enterprise efficiency, the improvement of efficiency is reflected in the outward shift of the production frontier and the close proximity of actual output to potential output [45]. From the perspective of digital transformation, information technologies can build an intelligent decision-making system and management system to improve the efficiency of the production, operation and management process for enterprises [46]. Therefore, digital transformation improves the timeliness of internal communication and reduces the coordination costs among production, transportation, storage and other departments [47]. From this point, we can infer that digital transformation will shift the enterprise production frontier outward, which means the enterprise will see greater potential output with the same input factors, significantly improving efficiency and corporate sustainability. In addition, digital transformation can help enterprises evolve from static organizations to dynamic organisms, respond quickly and flexibly to the latest market trends, improve the timeliness and accuracy of enterprise decision-making and realize efficient operations [48,49]. Specifically, in terms of production management, enterprises can obtain real-time production, transportation and storage information through digitization, obtain synchronous updating and tracking of production materials and build flexible supply chains by using big data to capture and forecast market demand fluctuations in advance [41]. In addition, based on customer demand, product parameter digitization and test virtualization, enterprises can conduct digital simulations of the R&D process to reduce trial-and-error costs as well as R&D costs [49]. Digital transformation integrates emerging technologies with traditional production factors, optimizes production and operation modes [25], improves management efficiency [26] and establishes a competitive advantage. Therefore, digital transformation can improve the efficiency of operations, R&D and management in enterprises and bring the actual output close to the production frontier. Based on these arguments, we propose the following hypothesis:

Hypothesis 3a. *Digital transformation will improve corporate sustainability by promoting corporate efficiency.*

Based on the theory of dynamic capability, an open system, such as an enterprise's organization, absorbs and integrates resources by virtue of perception ability, capture ability and transformation ability [30], and then improves innovation ability. Thus, enterprises can obtain a sustainable competitive advantage in a dynamic, complex and uncertain environment. Digital transformation helps enterprises promote innovation by accurately grasping demand, reducing costs and accumulating data resources to obtain a sustainable competitive advantage. With an investigation of 938 companies in various industries from Portugal, it is found that innovation capability and performance can be improved with digital transformation [50]. The popularization of digital technology in enterprises will break inherent boundaries, realize the innovation of business models and further tap customers' potential deep-seated needs [51]. Artificial intelligence enables enterprises to conduct more forward-looking analyses of market demand in the early stages of R&D and design new products or services that best meet customer needs on the basis of reducing the risk of R&D commercialization failure; thus, it greatly improves the motivation for innovation [52]. Due to the characteristics of long-term uncertainty and high risk of R&D, enterprises tend to reduce investment in R&D to avoid risks [53], whereas digitization can greatly improve the ability to forecast demand through the accumulation and analysis of data [54]. In addition, digitization helps enterprises realize intensive information processing and maintain databases, which improves their ability to create new applications or products from existing technologies, accumulate resources and information and enhance the efficiency of R&D. Digital transformation can also provide new methods for R&D innovation in enterprises; thus, it improves the essence of the innovation process [52]. Compared with the innovation of only one product, the innovation of a method can have a more extensive and far-reaching influence on various production fields [55]. Digital transformation further strengthens the enterprise's perception ability, capture ability and transformation ability and promotes enterprise innovation by using digital resources to cultivate different dynamic capabilities. Therefore, we propose the following hypothesis:

Hypothesis 3b. *Digital transformation will improve corporate sustainability by promoting corporate R&D.*

The logical framework of this paper is shown in Figure 1.

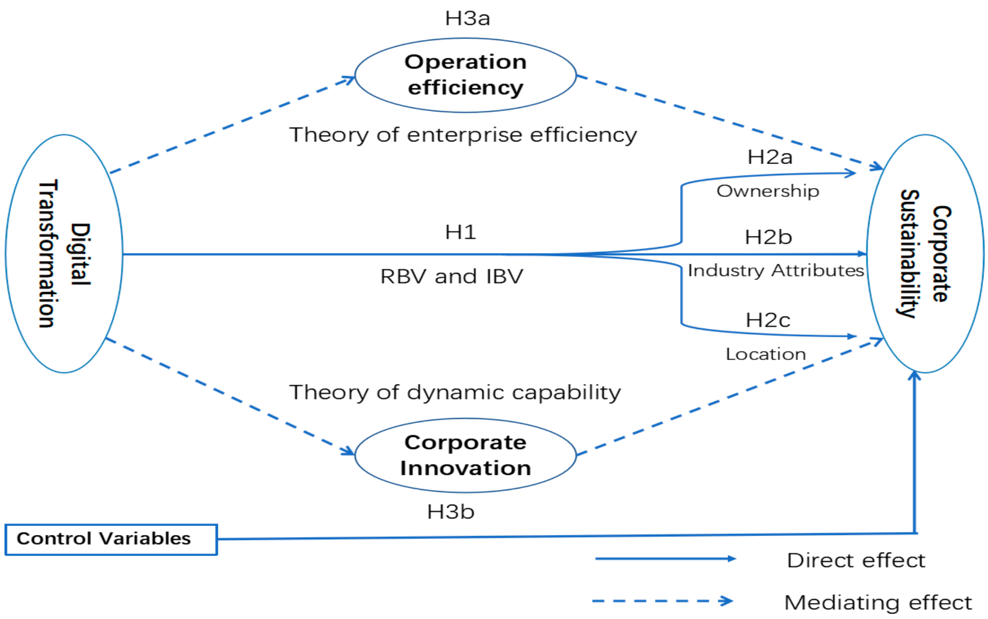

Figure 1. The logical framework and hypotheses.

3. Data, Variables and Models

3.1. Data and Sample

To explore the impact of digital transformation on corporate sustainability, this study took China's A-share listed companies as a research sample to carry out empirical tests. All of the data are from the CSMAR database. To ensure the accuracy of the research, we cleaned the data according to the following standards: (1) we excluded financial listed enterprises due to the particularity of the company's financial statements; (2) to ensure reliability, we excluded enterprises that received special treatment and delisted enterprises in the sample period; (3) samples with substantial missing data were also excluded. All continuous variables were tailed at the 1st and 99th percentile to reduce the disturbance of outliers. We retained 11,294 observations, and the distribution of sample characteristics is shown in Figure 2. In our sample, state-owned enterprises accounted for 27.69% of the total, and private enterprises for 67.35%. Regarding industry attributes, manufacturing enterprises accounted for 69.49% of the total, service enterprises for 21.23% and enterprises in other industries for 9.28%.

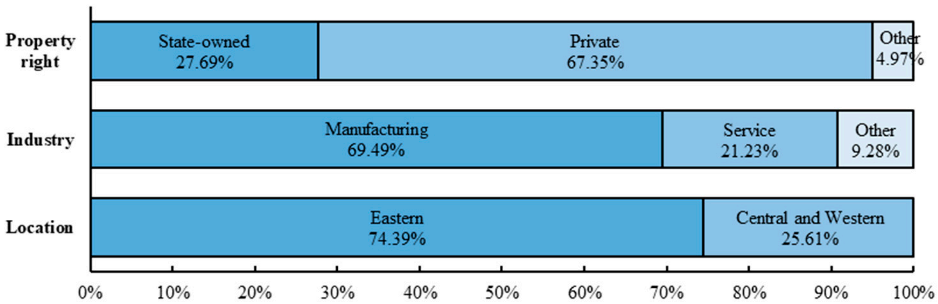

Figure 2. Sample distributions.

3.2. Variable Description

3.2.1. Corporate Sustainability

Sustainability refers to the ability of corporations to enact sustainable operations, long-term profitability, lasting competitiveness and stable growth. Researchers usually measure sustainability based on the sustainable growth model proposed by Higgins or Van Horne. Although the Higgins model may be simple and feasible, it does not consider the dynamic growth of enterprises [55]. Therefore, we used the Van Horne Sustainable Growth Model to build the sustainability index from profitability, the capacity to accumulate development funds, long-term solvency and operating capacity. The formula to calculate the index is as follows:

$$\text{Sustainability} = \text{net sales profit rate} \times \text{earnings retention rate} \times (1 + \text{equity ratio})/[1/\text{total asset turnover rate-net sales profit rate} \times \text{earnings retention rate} \times (1 + \text{equity ratio})] \times 100 \quad (1)$$

3.2.2. Digital Transformation

In the literature, researchers measure corporate digital transformation based on quantitative methods or textual analysis. The former method uses capital investments or the achievement of value from the process of enterprise digital transformation to construct the index [56], whereas the latter method is based on the frequency of keywords related to digital transformation appearing in specific textual materials such as enterprise annual reports [57]. The keywords mainly refer to R&D and the application of the new generation of information technology, such as artificial intelligence, big data and blockchain technology, which can reflect strategic characteristics and future prospects of enterprises [57]. Based on word frequency statistics, the CSMAR database provides digital transformation measurement data for listed companies, covering five technologically based subindicators of artificial intelligence, cloud computing, blockchain technology, big data and digital technology applications in corporate annual reports. In view of its accuracy and authority, we took the CSMAR database as the data source for the variable Digital.

3.2.3. Mediator Variable

To test the mediating role of efficiency and innovation in the impact of digital transformation on the sustainability of enterprises, this study conducted an empirical study based on the theory of enterprise efficiency and dynamic capability with operational efficiency and innovation as mediating variables. Because the operating cost rate of an enterprise can reflect the operating quality of the enterprise and its comprehensive control over operating costs, we referred to Lei et al. (2012) and took the inventory turnover as the proxy indicator of enterprise operation efficiency [58]. At the same time, referring to the research by Hong et al.(2022) [59], we took the intensity of enterprise R&D investment as the proxy of enterprise innovation. The definitions of the variables are as follows:

Efficiency was measured using the inventory turnover expressed as the ratio of operating cost to average inventory balance of the closing one and the opening one. A higher inventory turnover was regarded as higher operation efficiency for the enterprise.

Innovation was expressed using the intensity of enterprise R&D investment, which was calculated using the ratio of R&D investment to operating revenue in the current year.

3.2.4. Control Variables

We controlled the other characteristic variables that may affect corporate sustainability to avoid estimation bias from variable omission, including enterprise size (Size), debt to assets ratio (Leverage), enterprise risk (Risk), profitability (ROA), growth rate (Growth), listed age (ListedAge), size of board of supervisors (SBS), ownership concentration of shareholders (SHR), proportion of independent directors (IDR) and the duality of the CEO as chairperson (Dual). The definitions and descriptive statistics of the variables are shown in Tables 1 and 2.

Table 1. Definition of variables.

Type	Variable	Definition	Measurement
Explained variable	Sustainability	Ability to generate sustainable development	Shown in Formula (1)
Core explanatory variable	Digital	Digital transformation	Natural logarithm of the frequency of the key terms “artificial intelligence technology”, “cloud computing”, “blockchain technology”, “big data” and “digital technology applications” in corporate annual reports
Mediator variable	Efficiency	Operation efficiency	The ratio of operating cost to average inventory balance
	Innovation	Research and development	R&D inputs on operating revenues ratio as a percentage
Control variable	Size	Enterprise size	Natural logarithm of total assets
	Leverage	Debt to assets ratio	Ratio of total liabilities to total assets
	Risk	Degree of total leverage	Change in earnings per common share on change in production and sales
	ROA	Profitability	Ratio of net income to total assets as a percentage
	Growth	Growth rate	The ratio of the increase in the current year’s operating income to the total operating income of the previous year
	ListedAge	Listed age	The number of years the company has been listed
	SBS	The size of board of supervisors	The number of members on the board of supervisors
	SHR	Ownership concentration of shareholders	The percentage ownership of the largest shareholder
	IDR	The proportion of independent directors	The ratio of the number of independent directors to board size as a percentage
	Dual	The duality of CEO and chairperson	If a firm’s CEO and chairperson is the same individual, the value is 1 and 0 otherwise

Table 2. Descriptive statistics of variables.

Variables	N	Mean	SD	Min	Max
Sustainability	11,294	7.0349	6.1277	−2.6126	35.0790
Digital	11,294	16.1880	26.5136	1	153
Efficiency	11,294	14.3913	56.4143	0.0000	480.4879
Innovation	11,294	5.1322	5.3516	0	76.3497
Size	11,294	1.7765	8.7268	0.0074	243.2558
Leverage	11,294	0.3923	0.1883	0.0604	0.8405
Risk	11,294	2.0966	2.0445	0.9098	14.7495
ROA	11,294	0.0541	0.0405	0.0020	0.2052
Growth	11,294	0.1983	0.3848	−0.3953	2.4993
ListedAge	11,294	9.4759	7.3777	0.0822	26.4575
SBS	11,294	3.4123	0.9015	3	7
SHR	11,294	33.8659	14.5133	8.4300	73.8200
IDR	11,294	37.8795	5.3883	33.3300	57.1400
Dual	11,294	0.3288	0.4698	0	1

3.3. Regression Models

First, we constructed the model of the effect of digital transformation on corporate sustainability as follows:

$$Sustainability_{it} = \alpha_0 + \alpha_1 Digital_{it} + \sum \alpha_n Control_{it} + \sum Year_t + \varepsilon_{it}, \quad (2)$$

where the subscripts *i* and *t* represent the company and the year, respectively. The estimation of the coefficient α_1 reflects the marginal effect of digital transformation on corporate sustainability. *Control* includes a series of control variables. *Year* means the fixed effect of the year. ε is the random error term.

Second, to further identify the mechanism of the impact in reference to the mediating effect test procedure used by Wen et al. (2004) [60], we constructed the following models:

$$Sustainability_{it} = \alpha_0 + \alpha_1 Digital_{it} + \sum \alpha_n Control_{it} + \sum Year_t + \varepsilon_{it1}, \quad (3)$$

$$Mediator_{it} = \beta_0 + \beta_1 Digital_{it} + \sum \beta_n Control_{it} + \sum Year_t + \varepsilon_{it2}, \quad (4)$$

$$Sustainability_{it} = \gamma_0 + \gamma_1 Digital_{it} + \gamma_2 Mediator_{it} + \sum \gamma_n Control_{it} + \sum Year_t + \varepsilon_{it3}, \quad (5)$$

where *Mediator* represents the relevant mediator variable, and the other variables are set in accordance with the benchmark model in Equation (2). Based on Hypothesis 2, econometric identification was conducted from the perspectives of operation efficiency and innovation using Equation (3) to test the relationship between *Digital* and *Sustainability*, and then Equation (4) and Equation (5) were used to verify the corresponding mechanisms. The parameters α_1, β_1 and γ_2 should simultaneously pass the significance test. If not, we then used the *Sobel Z* statistic to test whether the mechanism is tenable.

In addition, we further analyzed the contribution of the two mechanisms. Referring to the framework for mechanism analysis based on the marginal effect proposed by Wang et al. (2022) [61], the premise of the application is that the number of explained variables should be greater than the number of mechanism variables. Therefore, five subdivided indicators of digital transformation were used, involving artificial intelligence, cloud computing, blockchain technology, big data and digital technology applications. The superscript s in the following equation is the mechanism variable.

$$\alpha_j = \theta_s \beta_j^s + e_j \quad s = 1, 2 \quad (6)$$

Taking the five subdivided indices of digital transformation into empirical testing, α_j and β_j^s were estimated through Equation (4) and Equation (5), and then the regression analysis and Shapley value decomposition of Equation (6) were carried out to obtain the degree of contribution for each mechanism in the influence of digital transformation on corporate sustainability.

Finally, to identify the possible heterogeneity of the impact of digital transformation on corporate sustainability, we conducted further empirical tests according to property rights, industry attributes and geographical location.

4. Estimation and Analysis

4.1. Benchmark Regression Results

We present the regression results for the benchmark model in Table 3. Control variables are included in the regression in Columns (3) and (4) but not in (1) and (2). According to the results, the coefficients of Digital were positive and significant at the 1% statistical level, indicating that the digital transformation of enterprises was beneficial to the improvement of sustainability. These findings are consistent with H1. From the results in Columns (3) and (4), it was found that the sign and significance of the estimated coefficients of each control variable were basically consistent regardless of whether the year fixed effect was controlled. Specifically, *Size*, *Risk*, *SBS* and *SHR* had significantly negative effects on sustainability, whereas *Leverage*, *ROA*, *Growth* and *ListedAge* had significantly positive effects.

Table 3. Digital transformation and corporate sustainability.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Digital	0.269 ***	0.263 ***	0.167 ***	0.175 ***
	(4.27)	(4.13)	(5.07)	(5.23)
Size			−0.143 **	−0.130 **
			(−2.17)	(−1.97)
Leverage			15.147 ***	15.157 ***
			(30.44)	(30.41)
Risk			−0.255 ***	−0.257 ***
			(−10.44)	(−10.50)
ROA			125.119 ***	125.231 ***
			(42.40)	(42.22)
Growth			1.422 ***	1.408 ***
			(11.31)	(10.95)
ListedAge			0.040 ***	0.040 ***
			(4.11)	(4.15)
SBS			−0.188 ***	−0.195 ***
			(−3.27)	(−3.38)
SHR			−0.025 ***	−0.026 ***
			(−6.36)	(−6.45)
IDR			0.010	0.011
			(0.98)	(1.02)
Dual			0.115	0.125
			(1.13)	(1.23)
Constant	6.537 ***	6.643 ***	−1.874	−1.688
	(47.50)	(30.50)	(−1.40)	(−1.26)
Year FE	No	YES	No	YES
N	11,294	11,294	11,294	11,294
R^2	0.004	0.004	0.671	0.672

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. The *t* values in parentheses were obtained with the robust standard errors clustered at the firm level.

4.2. Robustness Test for Endogeneity

There may be potential endogeneity in the regression from mutual causality, measurement error or sample selection bias. We re-estimated the nexus of digital transformation and corporate sustainability with alternative estimations.

4.2.1. Robustness Test with 2SLS

There may be potential endogeneity from mutual causality; that is, whereas digital transformation improves the sustainable development of enterprises, enterprises with strong indices of sustainable development may also be more inclined to carry out digital transformation. Therefore, we used the 2SLS regression method to avoid potential endogeneity. Specifically, we utilized the following three ways to construct instrumental variables. First, digital transformation was lagged for one period to eliminate potential endogeneity because sustainability in the current period cannot affect the enterprise's decisions about digital transformation in the previous period. Second, with reference to the existing research [41], considering the correlation between the individual behavior of enterprises and the overall behavior of peers, the average digital transformation level of peers (the average level of the digital transformation of other enterprises in the same industry excluding the focal enterprise) was constructed as an instrumental variable with the advantage of exogenous conditions. Third, according to existing research, the spherical distance from the city where the company is located to Hangzhou [2] and the city's level of Internet development [62] were used as instrumental variables to conduct 2SLS estimation. The basis is that Hangzhou, as a highly developed city central to the digital economy industry in China, has gathered abundant digital technologies such as the "big smart cloud area". A closer distance to Hangzhou for the listed companies and a higher level of urban Internet development may lead to a greater likelihood that the enterprise will implement digital transformation. Specifically, the distance data between each city and Hangzhou came from the calculation of the longitude and latitude of the city center, and the Internet development level of cities was a dummy variable in which the top 10 cities with the most developed Internet were marked as 1, including Hangzhou, Shenzhen, Guangzhou, Zhuhai, Xiamen, Nanjing, Shanghai, Beijing, Wuhan and Suzhou, and the rest were 0. Considering that the Internet development of cities is related to the digital transformation of enterprises and has no direct relationship with corporate sustainability, these strictly exogenous variables met the requirements for instrumental variables. The results of the first stage and the second stage are shown in Table 4. Columns (1) and (2) are the regression results with one-period lagged Digital and the peer level of Digital as the instrumental variables, respectively. Column (3) is the result with the focal city's Internet development level and the spherical distance to Hangzhou as the instrumental variables.

Table 4 shows that the F values of the three regressions were 19146.5, 1632.18 and 75.186, all of which were higher than the threshold value of 10, which means that the null hypothesis of weak instrumental variables is rejected. The Hansen J value in Column (3) was not significant, verifying the validity of the instrumental variables through an overidentification test. The coefficients of Digital in Columns (1) to (3) were significantly positive at the significance level of 1%. After considering the endogeneity problem, the significance and positive effect of core variables remained the same, and the coefficients and significance of other control variables did not fluctuate remarkably. It can be verified that the estimation results are relatively reliable and further prove that digital transformation is conducive to the improvement of corporate sustainability.

Table 4. Digital transformation and corporate sustainability: 2SLS regression.

Variables	(1)		(2)		(3)	
	IV1: One-Period Lagged *Digital*		**IV2: Average *Digital* Level of Peer Enterprises**		**IV3: (1) Focal City's Internet Development Level; (2) The Spherical Distance to Hangzhou**	
	First Stage	**Second Stage**	**First Stage**	**Second Stage**	**First Stage**	**Second Stage**
L.Digital	0.850 ***					
	(138.37)					
DTbar			0.050 ***			
			(40.40)			
HZdistance					0.074 *	
					(1.77)	
CityInternet					0.597 ***	
					(12.26)	
Digital		0.192 ***		0.338 ***		0.463 ***
		(4.11)		(5.71)		(2.60)
Size	0.002	−0.088	0.142 ***	−0.142 **	0.088 ***	−0.159 **
	(0.30)	(−1.23)	(7.63)	(−2.14)	(3.88)	(−2.28)
Leverage	−0.076	15.377 ***	−0.185	15.210 ***	−0.470 ***	15.285 ***
	(−1.31)	(28.83)	(−1.50)	(30.47)	(−3.22)	(30.12)
Risk	−0.018 ***	−0.275 ***	−0.030 ***	−0.248 ***	−0.045 ***	−0.240 ***
	(−3.27)	(−9.61)	(−3.91)	(−10.03)	(−5.18)	(−9.17)
ROA	−0.247	126.298 ***	−0.358	125.327 ***	−0.928 *	125.567 ***
	(−1.10)	(37.63)	(−0.73)	(42.35)	(−1.71)	(42.68)
Growth	0.103 ***	1.358 ***	0.120 ***	1.398 ***	0.172 ***	1.360 ***
	(3.25)	(8.68)	(3.54)	(10.85)	(4.60)	(10.35)
ListedAge	−0.003 **	0.025 **	−0.003	0.042 ***	−0.009 **	0.044 ***
	(−2.56)	(2.24)	(−0.89)	(4.27)	(−2.55)	(4.40)
SBS	−0.006	−0.172 **	−0.087 ***	−0.176 ***	−0.093 ***	−0.164 ***
	(−0.66)	(−2.51)	(−4.23)	(−3.02)	(−3.54)	(−2.69)
SHR	−0.002 ***	−0.030 ***	−0.005 ***	−0.024 ***	−0.012 ***	−0.022 ***
	(−3.45)	(−6.11)	(−3.55)	(−5.80)	(−7.60)	(−5.00)
IDR	−0.000	0.015	−0.001	0.009	0.001	0.009
	(−0.06)	(1.18)	(−0.19)	(0.88)	(0.34)	(0.86)
Dual	0.053 ***	0.146	0.090 **	0.105	0.090*	0.090
	(3.04)	(1.16)	(2.26)	(1.02)	(1.89)	(0.84)
Constant	0.635 ***	−3.328 **	−1.516 ***	−1.823	0.375	−1.802
	(3.74)	(−2.18)	(−3.88)	(−1.36)	(0.79)	(−1.34)
Year FE	YES	YES	YES	YES	YES	YES
N	7,350	7,350	11,236	11,236	11,294	11,294
R^2	0.738	0.691	0.316	0.670	0.099	0.668
Wald F test	19146.5		1632.18		75.186	
Hansen J test						0.007 [0.933]

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The *t* values in parentheses were obtained with the robust standard errors clustered at the firm level. The *p*-value of Hansen J Statistic is in the square bracket.

4.2.2. Robustness Checks with Variable Replacement, Changing Period and Heckman Two-stage Estimation

To avoid potential endogeneity from measurement error and sample selection bias, we re-estimated the models in three ways: variable replacement, changing the sample period and using Heckman's two-stage estimation.

First, dummy variables were used as proxies for enterprise digital transformation. Specifically, digital transformation was divided into five dimensions: artificial intelligence, cloud computing, blockchain technology, big data and digital technology application. To avoid the possible bias of a single quantitative method, two types of measurement were considered. First, if the enterprise had only made a digital transformation in one or two dimensions, then *Digital* was defined as 0; otherwise, it was defined as 1. Second, if the degree of digital transformation was lower than the median of 10, *Digital* was defined as 0; otherwise, it was defined as 1. Then, we substituted the dummy values into the model to obtain regression results, as shown in Table 5. According to the results in Table 5, the regression coefficients of *Digital* were still significantly positive at the statistical level of 1%, which is consistent with the previous results. In addition, considering that enterprises with stronger sustainable development capabilities tend to have higher sustainable growth rates, we used growth rate as the proxy of sustainability. The measurement of sustainable growth rates is as follows:

$$\text{Sustainable growth rate} = \text{return on net assets} \times \text{earnings retention rate} \quad (1 - \text{return on net assets} \times \text{earnings retention rate}) \tag{7}$$

Table 5. Robustness checks.

Variables	**Variable Replacement**			**Sample Period Change**		**Regression Method**
	(1) Digital Dimension	**(2) Digital Degree**	**(3) Sustainable Growth Rate**	**(4) 5-Year**	**(5) 10-Year**	**(6) Heckman**
Digital	0.374 ***	0.174 ***	0.182 ***	0.162 ***	0.178 ***	0.178 ***
	(3.87)	(5.20)	(5.02)	(5.14)	(5.33)	(5.33)
IMR					2.383 ***	2.383 ***
					(3.57)	(3.57)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	11,294	11,294	9,295	12,879	11,294	11,294
R^2	0.671	0.672	0.665	0.675	0.672	0.672

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The *t* values in parentheses were obtained with the robust standard errors clustered at the firm level.

The regression results with the variable of sustainable growth rates are shown in Column (3). This indicates that the conclusion is still robust.

Second, considering that the keywords related to digital transformation may change over time, which may lead to the omission of the right keywords related to digital transformation in word frequency capture, this paper adopted the method of sample reduction and expansion to eliminate the possible bias caused by the selection of sample duration. We reduced the sample to a 5-year sample group from 2016 to 2020 and expanded to a 10-year sample group from 2011 to 2020. The regression results are listed in Columns (4) and (5) in Table 5. The significance level and direction of *Digital* remained unchanged, indicating that the conclusions of the previous regression are robust in the selection of sample duration.

Third, the benchmark regression conclusion may be disturbed due to self-selection bias in the sample; that is, the digital transformation of enterprises may be the result of the proactive decisions of enterprises that already have great sustainability. Therefore, we used Heckman's two-stage estimation to check the robustness. Referring to Yang and Liu (2018), size and operating cost were used as the key factors for enterprises to carry out digital transformation to estimate the inverse Mills ratio (*IMR*), and then we conducted the regression of the second stage. Column (6) in Table 5 shows the results of the second stage with a significantly positive coefficient of *IMR*. After controlling for the influence of *IMR*, the regression coefficient of digital transformation was significantly positive at the statistical level of 1%, which further indicates the robustness of the empirical results in this paper.

4.3. Heterogeneity

To examine the heterogeneous impact of digital transformation on sustainability from the aspects of property rights, industry attributes and geographical location, we further used a fixed effect model and 2SLS estimation method to regress based on subsamples. The results are shown in Table 6.

Table 6. Tests for heterogeneity: property rights, industry attributes and geographical location.

Panel A	**State-Owned**				**Private**			
Variables	(1) FE	(2) IV1	(3) IV2	(4) IV3	(5) FE	(6) IV1	(7) IV2	(8) IV3
Digital	0.000	0.027	0.044	−0.009	0.204 ***	0.239 ***	0.384 ***	0.531 ***
	(0.01)	(0.33)	(0.43)	(−0.02)	(5.09)	(4.21)	(5.41)	(2.98)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	3127	1979	3046	3127	7606	4935	7534	7606
R^2	0.699	0.702	0.699	0.699	0.687	0.710	0.689	0.682
Panel B	**Manufacturing Industry**				**Tertiary Industry**			
Variables	(1) FE	(2) IV1	(3) IV2	(4) IV3	(5) FE	(6) IV1	(7) IV2	(8) IV3
Digital	0.137 ***	0.149 **	0.217 *	0.601 **	0.068	0.088	0.032	−0.717
	(3.00)	(2.19)	(1.68)	(2.15)	(1.14)	(1.13)	(0.27)	(−1.06)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	7848	5021	7843	7848	2398	1606	2367	2398
R^2	0.659	0.666	0.659	0.651	0.722	0.780	0.723	0.697
Panel C	**Eastern regions**				**Central and Western Regions**			
Variables	(1) FE	(2) IV1	(3) IV2	(4) IV3	(5) FE	(6) IV1	(7) IV2	(8) IV3
Digital	0.181 ***	0.209 ***	0.344 ***	0.379 *	0.106	0.072	0.243 **	1.072
	(4.71)	(3.91)	(4.93)	(1.88)	(1.60)	(0.73)	(2.24)	(1.43)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	8402	5544	8342	8402	2892	1799	2804	2892
R^2	0.683	0.700	0.682	0.681	0.631	0.653	0.628	0.595

Note: (1) ***, ** and * indicate 1%, 5% and 10% significance, respectively. The *t* values in parentheses were obtained with the robust standard errors clustered at the firm level. (2) In the regression of the 2SLS method, the instrumental variable in IV1 is represented by one-period lagged Digital, and in IV2, it is the average *Digital* level of peer enterprises. In IV3, the focal city's Internet development and its spherical distance to Hangzhou are regarded as the instrumental variables. (3) In the results of the heterogeneity test of property rights and industry attributes, the sample of other properties only accounts for 4.97%, and the sample of other industries only accounts for 9.28%. The samples are small and not representative; thus, the regression results are not listed.

Panel A shows the results for the heterogeneity of state-owned and private property rights. The regression coefficients of *Digital* in a sample of state-owned enterprises were nonsignificant, whereas they were significantly positive at the 1% statistical level based on a sample of private enterprises. The results are still robust under different regressions, which shows that compared with state-owned enterprises, private enterprises see a more significant role for digital transformation in promoting sustainability. Therefore, we cannot reject H2a.

Panel B shows the results of industry heterogeneity. This indicates that in the manufacturing industry, digital transformation had a significant positive impact on the sustainability of enterprises. This relationship does not exist in the sample of tertiary industries. This finding tells us that compared with the tertiary industry, the manufacturing industry saw a more significant impact from digital transformation on sustainability, which is consistent with H2b. In view of this result, we believe that manufacturing enterprises have more complicated production links, higher requirements for product differentiation and stricter control over cost and innovation. Therefore, information technologies such as artificial intelligence can be applied to manufacturing for faster and more effective results. In other industries, the relationship between enterprise operation and information technology was relatively weak, and thus, digital transformation has less impact on the sustainability of these enterprises.

Panel C shows the results for location heterogeneity. Despite the result of IV3 with 10% significance level, the coefficients of *Digital* based on the sample of enterprises in the eastern region were significantly positive at the 1% statistical level. Although the regression coefficient of the core variable *Digital* for the sample of enterprises in the central and western regions was positive, the significance level was unstable, and the marginal effect was weaker than that seen in the eastern regions. This shows that compared with the central and western regions, the eastern region saw a significant and more robust positive impact on sustainability from digital transformation. Therefore, we cannot reject H2c. In China, there are large regional differences in economic development and in the business environment. We believe that there is more favorable ground for digital transformation in the eastern region, and that enterprises have better technical conditions and talent reserves, which are conducive to displaying the effects of digital transformation.

5. Further Discussions on Mediating Effect

To test the mediating effects of improving operation efficiency and promoting enterprise innovation in the process of digital transformation enhancing the sustainability of enterprises, we further regressed Models (2)–(4). The regression results are shown in Table 7. Among them, the results in Column (1) show that digital transformation had a significant positive impact on the sustainability of enterprises. Column (2) shows that the regression coefficient of *Digital* to *Efficiency* was 4.575 and significant at the 1% statistical level, indicating that enterprises' digital transformation can help improve operation efficiency. In the results of Column (3), the coefficients of digital transformation and operating efficiency are shown as significantly positive, which indicates that they had significant positive impacts on the enterprise's sustainability. These results prove that improving operation efficiency is an important mechanism to allow the enterprise's digital transformation to affect its sustainability. Therefore, we cannot reject H3a.

Table 7. The mediating effect test of operation efficiency and innovation.

Variables	Benchmark	Operation Efficiency		Corporate Innovation	
	(1) Sustainability	(2) Efficiency	(3) Sustainability	(4) Innovation	(5) Sustainability
Digital	0.175 ***	4.575 ***	0.158 ***	0.996 ***	0.142 ***
	(5.23)	(5.22)	(4.73)	(12.85)	(4.03)
Efficiency			0.004 ***		
			(3.56)		
Innovation					0.033 ***
					(3.26)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	11,294	11,294	11,294	11,294	11,294
R^2	0.672	0.020	0.673	0.233	0.672

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The *t* values in parentheses were obtained with the robust standard errors clustered at the firm level.

There are two main ways for enterprises to achieve efficiency increase through digital transformation. One is to achieve more efficient supply and demand matching with upstream and downstream industries in order to reduce information asymmetry and reduce transaction costs in production. The second is to build an integrated digital communication system platform within the enterprise to achieve collaboration and linkage between departments, thereby increasing labor productivity. For some manufacturing enterprises, digital simulation can also effectively reduce trial and error costs, thereby reducing research and development costs, helping enterprises to invest limited resources in the implementation of strategies and improving sustainability. Similarly, the results of Columns (4) and (5) show that the coefficient of *Digital* to *Innovation* and the coefficients of both to *Sustainability* were significantly positive at the 1% statistical level, indicating that enterprises can improve enterprise innovation through digital transformation and then enhance corporate sustainability. These findings are in line with H3b.

To further discuss the mechanism based on the marginal effect, we first regressed the five subdimensions of enterprise digital transformation on the explained variables *Sustainability* and the mediator variables with the fixed effect method. We obtained the marginal effects of the different dimensions on *Sustainability*, *Efficiency* and *Innovation*. Then, combining the estimated coefficients, we conducted a regression analysis with Equation (6) and used the Shapley value decomposition method to quantify the contribution degree of the *Efficiency* and *Innovation* mechanisms. The results are shown in Table 8; 38% of corporate sustainability can be explained with these two mechanisms. Enterprise innovation was the main transmission mechanism, accounting for 51.8%, whereas operational efficiency accounted for 48.2%.

Table 8. Contribution decomposition of each mechanism.

Mechanism Variables	Sustainability	
	R^2	Contribution
Efficiency	0.183	48.20%
Innovation	0.197	51.80%
Total	0.380	100.00%

6. Implications and Discussion

Considering that less attention is given to the nexus of digital transformation and corporate sustainability, we contribute to the literature by taking digital transformation as a new perspective for explaining and understanding corporate sustainability, which fills the gap because the discussions in previous research stem mainly from managerial perspectives of internal corporate governance mechanisms. We also contribute by constructing a novel theoretical framework combining the resource-based view (RBV), institution-based view (IBV), enterprise efficiency theory and dynamic capability theory and empirically exploring whether there exists a positive relationship between digital transformation and corporate sustainability. The heterogeneous effects of ownership, industry and location on the nexus of digital transformation and corporation sustainability were considered. Furthermore, we tested the mediating effects of operation efficiency and innovation in the impact of digital transformation on corporate sustainability. Methodologically, we tried to solve potential endogeneity issues with different instrumental variables. We believe that the findings in this study have important practical implications for governments and managers.

First, governments must realize that digital transformation is an important means to improve corporate sustainability. It is also helpful for economic sustainability and resilience under the impact of the COVID-19 epidemic and turbulence internationally. Our findings send a message to policymakers that there is heterogeneity in ownership, industry and location in the ability of digital transformation to improve corporate sustainability. To maximize the effect of digital transformation on corporate sustainability, the government's supporting policy should be more biased toward private manufacturing enterprises in a relatively free market environment.

Second, managers can obtain inspiration from our findings by considering corporate ownership, industry and location in deciding whether to implement digital transformation. In addition, this study sends an important message to managers that in an institutional environment conducive to improving operation efficiency and stimulating innovation, a higher sustainability premium can be gained from digital transformation.

Like all other studies, our work has the following limitations, which provide opportunities for future research. First, our research took listed companies in emerging market economies as a sample, and the research conclusions may not be applicable to unlisted companies and those in developed economies. Using databases including unlisted companies and those from developed economies is encouraged for future research. Second, our sample period was 2014–2020. Whether the impact of the COVID-19 epidemic after 2020 affects the relationship between digital transformation and enterprise sustainability is not yet explainable with contemporary data. For future research, it would be interesting to explore how COVID-19 affects the digital transformation strategy of enterprises and its impact on enterprise sustainability. Third, in the discussion of endogenous issues, we only focused on the potential endogeneity of digital transformation, and we took the 2SLS estimation with different IVs to avoid potential bias. However, there may have been endogeneity in the mediating effect test [63]. In view of the complexity of this problem, we have not been able to deal with it. This is a very important and challenging issue and worthy of further study.

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