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The Effects of Digital Transformation on Firm Performance: Evidence from China's Manufacturing Sector

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Abstract: With vast potentials in improving operations and stimulating growth, digital transformation has aroused much attention from firms across the world. However, the high costs associated with the transformation can not be ignored. Limited research has looked into the organizational performance effects of digital transformation. After examining the benefits and costs of digital transformation, this research makes an empirical study on the impact of digital transformation on firm operational and financial performance. The panel data from 2010 to 2020 of 2254 manufacturing companies in China suggests that the intensity of digital transformation is in positive correlation with the process-based operating performance, and in the U-shaped correlation with the profit-oriented financial performance. Further, we find that digital transformation has a much more lasting impact on operating performance than on financial performance. The conditions required (i.e., policy and innovation environment) to improve the operating performance via digital transformation are more easing. This research shows the differentiated effect of digital transformation on different dimensions of organizational performance and provides guidance for companies to set the goals for digital transformation.

Keywords: digital transformation; firm performance; operating performance; financial performance; manufacturing sector; China

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1. Introduction

Pervasive digital technologies (e.g., internet of things, cloud computing, artificial intelligence, and big data analytics) are bringing about profound social and industrial changes [1–4]. The raging COVID-19 pandemic further accelerates the in-depth application of digital technologies. To stay competitive in the digital context, companies are stepping up their digital transformation (DT) worldwide. DT refers to the efforts made by companies to improve customer relationships, operational processes, or business models with digital technologies [5–8]. According to the survey launched among global industrial companies by Parametric Technology Corporation, 92% of the surveyed companies have started DT, hoping to foster competitive advantages [9]. However, not all companies are sure of the business values of DT, given the high costs it requires. In addition, existing research yields no definitive conclusions on the organizational performance effects of DT.

In information systems (IS) research, the business values of digital technologies have been widely recognized [10]. According to substantial work on IT valuation, the investment in or the use of digital technologies has proven to be productive in improving organizational performance, including the operating and financial performance [11–14]. The role of digital technologies in enabling internal operations of companies has attracted much attention in the IS research [15]. The rapidly advancing digital technologies keep unleashing potentials recently. They not only enable operations, but also stimulate product, service, and business model innovation [2,16,17]. In this sense, DT is not only potent to streamlining the process of business operations but to bringing about opportunities for value creation and business growth, thereby boosting profits. Unlike the local adoption of digital technologies in the past, DT involves the reconstruction of vision, processes, capabilities, organizational structure, and culture [5,6,18,19]. This means that the cost of DT is no longer about the conventional investment in digital technologies, but about the cost of integration and management resulting from business and organizational transformation [16,20]. Therefore, both the benefits and the costs of DT differ significantly from those of traditional IT use. Therefore, the organizational performance effects of DT remain uncertain.

Findings on the relationship between DT and organizational performance are mostly included in the reports generated by industrial consulting agencies [5,21–23]. These agencies have launched extensive surveys to learn about the operational and financial performance effects that companies care about most, but they have not made much explanation on the theoretical mechanism as for how DT affects organizational performance. As the samples and performance indicators used differ across surveys, no agreed results have been generated. Most academic papers focus on the effect of one specific digital technology on corporate financial performance [24–28]. These studies look at local organizational changes enabled by specific digital technologies. However, the current DT leads to company-wide changes driven by a combination of digital technologies [1,3,29]. Its benefits and costs far outweigh those of a single digital technology. It is, therefore, necessary to make an overall examination of the impact of DT on organizational performance.

This paper analyzes the impact of DT on firm performance in the dimensions of operating performance and financial performance. From the "benefit-cost" perspective, we explore the impact mechanisms of DT on business operational and financial performance. In terms of business operations, DT helps improve the efficiency of main business activities at the cost of fixed investment in digital technologies, talents, and services. These points of view can be mostly found in the IT valuation stream. Still, an outstanding feature about the benefits of DT is that the greater the DT, the stronger the "synergy" will be generated across digital businesses [30]. This further magnifies the marginal benefits. Hence, our study proposes that DT has a positive impact on operating performance. In addition to improved operation processes, DT has the potentials to bring about higher profitability thanks to firm growth driven by digital innovation and changes. Yet, rising management and integration costs reduce firm profits. It takes time before the marginal benefits outweigh the marginal costs, and positive net benefits are generated. It is therefore proposed that there is a U-shaped relationship between DT and firm financial performance.

Based on the text analysis of the annual reports of listed companies, this paper first makes a quantitative measurement of the intensity of DT. The test of the data of 2254 listed manufacturing companies (from 2010 to 2020) in China provides strong support for the propositions in this paper. Inspired by the strategy of "Smart Manufacturing" (similar to "Industry 4.0"), China has been promoting DT in the manufacturing industry for years, providing an ideal empirical setting for the research. Our study enriches the literature on the organizational performance effects of DT by exploring the differentiated effect of DT on operational and financial performance and provides guidance for firms to set the goals of DT. The U-shaped relationship between DT and firm financial performance solves the disputes over the economic values of DT in the theoretical and practical sectors. Further empirical analysis reveals that DT has a much more lasting impact on operating performance than on financial performance. In addition, the conditions required (i.e., government regulation and industry type) to improve the operating performance via DT are more easing. These findings clarify several boundary conditions under which DT affects firm performance.

2. Theory and Hypotheses

2.1. DT and Organizational Performance

The impact of DT is primarily assessed at the organizational level [4]. There is no doubt that DT is a powerful weapon for companies to build and maintain competitive advantages in the digital age [1,31]. As IT plays an enabling role in organizational operations, companies first hope to improve operating efficiency or reduce costs via DT [9,32]. Many studies show that DT helps improve specific business processes, such as services [33], sales [34,35], and supply chains [36]. Yet, less research has been done on the relationship between DT and operating cost or efficiency on the firm level.

As digital technologies continue to evolve, they not only enable existing businesses but foster new businesses [17]. DT not only enables business operations, but encourages innovation in products, services, and even business models [2,16]. Innovation and growth become the strategic goals of DT [9,22]. Companies wish to gain greater profits via digitalization. There is no affirmative conclusion on the relationship between DT and firm financial performance for now [37]. Compared with academic research, industry consulting agencies are more interested in identifying the financial performance effects of DT. Although the industry-focused reports lack sound theoretical bases, they provide empirical evidence. The survey on global companies by Capgemini Consulting showed that DT has significantly improved the financial indicators of companies, such as revenue, profitability, and market value [8]. However, according to McKinsey's global survey, only 20% of companies witnessed improved financial performance via DT [21], and this number dropped to 7% in Accenture's survey among Chinese companies [22].

Although it is critical to figure out the organizational performance outcomes of DT, little academic work on this topic has been done [38]. One possible explanation is that varying consequences of DT have distracted scholars [16]. The process-related intermediate results (e.g., user base growth and customer satisfaction) gain much attention [7,39]. For example, when examining the impact of DT on the Spanish automobile manufacturing industry, Llopis-Albert et al. [40] focused on the satisfaction of stakeholders. Although process-related metrics are crucial, the ultimate goal of DT should be better economic outcomes, such as operating costs or net profit margins.

Another possible explanation is that DT as a single comprehensive variable can be hardly measured. This makes empirical research focus on the financial performance outcomes of firm changes enabled by specific digital technologies. For example, Scott et al. [26] concluded that the adoption of the SWIT network system is positively correlated with the long-term profitability of banks. Duman and Akdemir [25] found that the transformation driven by Industry 4.0 technologies elevates the profitability and sales of companies. Research like this often looks at the economic benefits of specific digital technologies, while ignoring the cost of organizational change enabled by digital technologies. In practice, companies are enjoying the benefits brought about by the combination of digital technologies [1,3,29], while bearing the costs of such technologies-enabled organizational transformation. This explains why the organizational performance effects of DT are uncertain.

The potential benefits of DT have been much covered in academic research and business reports (Many literature assumes that DT will generate a positive impact when defining DT [4].), but few mention the costs of DT, which often requires heavy investment. According to Melrose et al. [9], most companies spend more than USD 1 million per year on DT projects, not including the hidden costs. This paper makes a thorough analysis of the benefits and costs of DT, and then explores its impact on firm performance. With reference to the commonly used measures of organizational performance in IT business value research [13,41,42] and to the performance goals of DT [4,5,32], this research classifies firm performance into the operating performance and the financial performance. The former measures the cost reduction or efficiency improvement in the operation processes of companies [42]. In this paper, we focus on the main business processes of companies (such as production and sales of products by industrial companies) where digitalization happens most in practice. The latter reflects the final outcomes of business operations and is normally profitability-oriented [26,43]. The next section explores the impact mechanisms of DT on the operational and financial performance based on the "benefit-cost" rationale.

2.2. DT and Firm Operating Performance

The enabling role of IT in the operational processes of organizations has been widely recognized [15]. Compared with the traditional role of IT, DT has a much stronger impact on business operations in terms of both scope and intensity. Björkdahl [32] pointed out that, instead of boosting growth, the current DT of companies focuses on improving the operating processes, i.e., the reduction of actual costs and the enhancement of work efficiency in main business activities.

DT improves business operations by reducing transaction costs, increasing employee productivity, improving asset efficiency, and optimizing the supply chain. To begin with, DT reduces the transaction costs in the production and sales processes. Under the management of a unified digital system or platform, the information flows efficiently within organizations, which helps improve the efficiency of communication between departments and processes and removes unnecessary links [44]. In addition, DT helps improve labor productivity. This is not only about the reduction of labor intensity resulting from automation [45], or the support to dynamic decision-making driven by data [46], but about the overall improvement of work efficiency brought about by organizational structure optimization [47]. Furthermore, DT elevates the efficiency of corporate assets. For example, enabled by artificial intelligence technologies, hardware, such as machines and equipment, is able to conduct independent learning and adjustment, ensuring optimal behaviors [48]. By simulating in real-time digital models, digital twins help equipment or production line to operate under the optimal scheme [49]. Last but not least, digitalized enterprises could synergize the supply chains. Digitalization makes it easier for companies to share the delivery, inventory, and production plans with suppliers, thereby optimizing the supply chains [50].

Despite the benefits, DT increases business operating costs, i.e., fixed investment in digital resources such as infrastructure, talent, and services. Firstly, organizations need to keep introducing the software and hardware related to the digital technology portfolios and ensure subsequent maintenance and upgrades, thereby supporting the digitization of the main business activities. As one of the production factors in the digital age, data assets require investment in its acquisition and management [30]. Second, organizations need to introduce professional talents excelling in digital technologies so as to support digital businesses [51]. Third, the outsourcing of certain digital services, including the traditional IT services and the new cloud services and machine intelligence costs [52]. Fourth, some companies set up independent subsidiaries to explore new digital businesses [6], leading to increased operating expenses.

Keeping in mind the operating costs, we focus on the net benefits of DT on business operations. The positive effects of IT investment on future operations of companies have long been verified [10,13]. Compared with traditional IT investment, DT requires more operational investment and brings about much more considerable benefits at the same time. The benefits increase as the intensity of DT deepens because a "synergy" will form among different digital units. For example, data is shared across all departments and processes so as to support end-to-end collaboration, thus reducing transaction costs. In addition to removing internal barriers, some leading digital companies are working on data collaboration and efficiency optimization along industrial chains [53]. When sufficient equipment data is gained, the algorithms will be able to make much more accurate predictions [30] so as to improve asset efficiency.

Therefore, despite the operating expenses, we contend that DT helps reduce operating costs and improve operating efficiency. It is proposed that:

Hypothesis 1 (H1). *DT is in a positive correlation with operating performance.*

2.3. DT and Firm Financial Performance

Financial performance reflects the final operating results of companies. Although improved operating processes contribute to better financial performance indirectly, DT is mostly launched in pursuit of profits by expanding the value space of companies. Unlike traditional IT, digital technologies today not only enable existing business but boost innovation and firm growth [2,16,17,22]. This allows DT to further elevate financial performance.

DT facilitates firm growth via digital marketing, product or service innovation, and business model changes. First, DT enhances the marketing capabilities of companies. By collecting massive user data online and profiling users based on big data analysis, companies will be able to understand and even predict user needs and preferences, and then perform precise product or service recommendations [37,54,55]. Second, DT facilitates product innovation. On the one hand, the combination of digital components and physical products leads to smartly interconnected products [56,57]; on the other, in the data-driven innovation processes, digital tools (e.g., 3D-printing, Digital Twin) help accelerate the development of new products and enable personalized customization [24,58]. For example, digital twins afford kinds of stakeholders a better chance to share real-time information and work together virtually toward problem-solving and product innovation [49]. Third, services carrying digital technologies will be fostered during DT. Servicization may first arise by providing operational and supplementary services for smart products [32]. With the elevation of the level of digitization, more advanced service offerings will emerge [59]. Fourth, DT has the potentials to reshape business models. The extensive application of digital technologies has fostered new business logic (e.g., platform or ecosystem) that help companies change the ways of value capturing and creation, enabling them to get adapted to environmental changes agilely [19,60,61].

DT does not guarantee profitability, because it incurs costs. In addition to operating costs, there are integration costs [16]. In the process of innovation driven by digitalization, organizational inertia needs to be removed [20,60], which will incur communication, coordination, or integration costs. First, companies need to ensure the coordination between their existing resources and capabilities and the digital ones [31,61]. Costs in this regard could come from the integration of emerging digital technology knowledge with the existing knowledge base [62], the response to massive data and information [30,63], the integration of the old and new information systems [35], the collaboration of IS and business leaders [64], and the adaptation of organizational structures [6]. Second, companies need to align managerial cognition and organizational culture to facilitate DT [65]. A common choice is to change the top management, such as introducing new senior executives (e.g., Chief Digital Officers) [66]. Third, there are costs from the reconciliation between companies and their business partners on digitization [67], and those from the changes in the roles along industrial chains [36]. Most of these costs are accrued for management expenses or non-operating expenses.

In view of the integration costs and the synergy, it is assumed that there is a curvilinear relationship between DT and firm financial performance. After the DT is launched, the integration costs will rise sharply, leading to a significant increase in management expenses [20]. Given that the full advantages of DT are yet to come, the integration costs will offset the contributions brought about by DT to business growth and operations [68]. In other words, when the intensity of DT is low, the marginal integration costs exceed the marginal benefits in business growth and operations. The increase in the intensity of DT has a negative net effect on financial performance. When the intensity of DT reaches a certain threshold, there will be synergy from different digital units, which not only helps improve operations as described in Section 2.2 but accelerates growth. Such synergy can fuel new forms of innovation and entrepreneurial initiatives that cross traditional sectoral boundaries and integrate digital and non-digital assets [68,69]. For example, if digital connections between marketing and R&D are built, the user data will be better used to guide product or service innovation and provide personalized customization [37]. The marginal benefits of DT in business growth and operations at this stage will make up for the integration costs. DT would then have a positive net effect on financial performance.

To sum up, firm financial performance declines to a certain point beyond which higher intensity of DT leads to an increase in financial performance. We propose the following hypothesis:

Hypothesis 2 (H2). *There is a U-shaped relationship between DT and firm financial performance.*

3. Method

3.1. Sample and Data Collection

Data from 2010 to 2020 of the manufacturing companies listed on the A-share market of China is used as a sample. The manufacturing sector shepherds DT. By focusing on the manufacturing industry, the systemic differences in DT across different industries will be removed. With the rapid development of digital technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence since 2010, business DT becomes popular worldwide [37,57]. According to a McKinsey survey in 2018, more than 80% of companies had launched DT over the past five years [21]. The manufacturing industry is no exception. Since 2010, major industrial powers in the world have formulated digital development strategies for the manufacturing industry, such as the "Advanced Manufacturing Partnership" in the United States, the "Industry 4.0" in Germany, and the "Industrial Value Chain" in Japan. China is facing the challenge of changing from a manufacturing source to a manufacturing power and has urgent needs for DT [48]. As early as 2010, the Chinese government began to accelerate the in-depth integration of informatization and industrialization. In 2015, "Made in China 2025" was proposed, with smart manufacturing as the focus.

We collect data through secondary sources including existing statistical databases and the annual reports of listed companies in China's manufacturing industry. The industry engaged in by a listed company is determined in accordance with the Guidelines for the Classification of Listed Companies (2012 Edition) issued by the China Securities Regulatory Commission. The Level-1 code of the manufacturing industry is C, and there are 30 Level-2 industries (codes) under it. The DT shall be measured based on the data in the companies' annual reports. The reports are downloaded from the official websites of the Shenzhen Stock Exchange and the Shanghai Stock Exchange. Other variables are relevant to company characteristics and financial information which are sourced from China Stock Market and Accounting Research Database (CSMAR).

We obtain 2356 companies in the initial sample by collecting annual reports of China's manufacturing companies. Then we search their financial data in the CSMAR database. Samples with data missing are eliminated. Finally, a total of 2254 companies are included in the empirical research. The sample companies are distributed across 29 (Level-2) industries. Table 1 lists the top 10 industries with the largest number of companies. The number of companies in these industries accounts for more than 75% of the full sample. In the data analysis, panel regression technic is adopted.

Table 1. Top 10 industries by number of sample companies.

Industry Code	Industry Name	Number of Firms
C39	Communication equipment, computer and other electronic equipment manufacturing	342
C26	Chemical raw materials and chemical products manufacturing	231
C38	Electrical machinery and equipment manufacturing	227
C27	Pharmaceutical manufacturing	219
C35	Flexible unit manufacturing	201
C34	Metal products manufacturing	130
C36	Dedicated equipment manufacturing	128
C30	Plastic products manufacturing	84
C29	Rubber products manufacturing	74
C32	Ferrous metal smelting and rolling processing	68

3.2. *Measures*

3.2.1. Dependent Variables

Organizational performance is classified into operating performance and financial performance in this research. Operating performance represents the efficiency of business processes, usually denoted as the cost-intensive effect [41,42]. We focus on the operating performance of a company's main business processes, calculated with the formula 1-(operating cost + sales expense)/operating income (i.e., cost of obtaining unit revenues). Financial performance is represented by the overall profitability of a company. Profitability-based metrics are a common choice to measure firm (financial) performance and are frequently used in the research on organizational performance effects of digital technologies [42,43,55]. The reports of industrial consulting agencies show that the contribution rate to profits is one of the major metrics used by companies to evaluate the returns of DT [23,53]. This paper takes the return on assets (ROA) as the proxy variable of financial performance, i.e., dividing a company's annual net profits by the total assets.

3.2.2. Independent Variable

The *intensity of DT* is the core independent variable of our study, which represents the degree of companies using digital technology to facilitate improvement in customer relationships, operational processes, or business models [5–8]. The intensity of DT reflects how active a company is in its engagement in digital business practices.. At present, little research has been done to make quantitative measurements of DT. As DT is a company-wide strategic change [18,39], it covers a large scope and can hardly be decomposed and quantified technically. By drawing on the measurement approaches of other behavioral variables in strategic management research, we try to indirectly characterize the intensity of DT via text analysis of the annual reports of listed companies.

A company's annual report is an official document that discloses the financial status and operating results of the company in a fiscal year. It not only covers financial indicators but reveals strategic choices [70]. If a company undergoes major strategic changes, the changes should be presented in the annual report. As annual reports are made public and carry much significance, companies are cautious with the choice of words. In the area of strategic management, there are many strategic behavior-related constructs, such as managerial cognition, measured based on the report contents (i.e., term frequency, tone, and readability) [71–73]. DT is an important strategic choice in the digital economy era, and relevant information should be covered in the annual report. As DT becomes an inevitable choice [9,37,74], companies have motives to disclose their digital actions in annual reports. This is particularly true in China (a country with a strong government) because companies tend to cater to the government's industrial digitization policies. Therefore, it is reasonable and feasible to mine information on a company's DT from annual reports. Sousa-Zomer et al. [43] has made a valuable experiment about this. They determined whether a company has launched DT initiatives by using keywords related to "digital" in annual reports.

In annual reports, the frequency of a term indicates its relative importance [75]. The word frequency method is the best choice for quantitative measurements based on large sample texts [76]. The strategic behavior variables mentioned above are measured by word frequency as well. Guided by this idea, we use the keyword frequency approach to quantitatively measure the intensity of a company's annual DT. This approach is effective under the prerequisite that the feature word set on DT in annual reports is accurately screened. To this end:

1. Choose keywords that best represent a company's DT behavior as the seed word. Smart manufacturing is the main goal with the highest priority of DT in the manufacturing industry. In China's manufacturing industry, "smart manufacturing" appeared earlier in written documents than "DT". This is true with the annual reports of listed manufacturing companies as well (the author searched all annual reports of listed manufacturing companies in China since 2001 and found that "smart manufacturing"

and "digital transformation" both first appeared in 2009. Before 2015, the frequency of the former was 395 times, while that of the latter was only 13 times). After "Made in China 2025" was proposed in 2015, smart manufacturing has been regarded as the main direction of DT [77]. "Smart manufacturing" is therefore chosen as the seed word.

2. Develop words similar to the seed word. We perform Chinese word segmentation with Word Embedding on annual reports. Construct a word semantic and syntactic similarity calculation model based on neural network training with WinGo Textual Analysis Database. The Database is the first artificial intelligence financial data platform in China that discloses the annual reports of companies listed in China and the U.S. Extract 30 words with the best similarity to the seed word from annual reports. After being manually screened by two industry experts, 24 words with a similarity of above 50% to the seed word are chosen. Repeat the above steps against the 24 chosen words until 53 keywords on DT are drawn.
3. Verify the validity of the keyword set. The correlation analysis of word frequency shows that words are highly correlated, most of which are significantly correlated with "smart manufacturing" at the significance level of 5% and above. Factor analysis is then made based on correlation analysis. Although the samples satisfy the conditions of factor analysis, not many common factors are extracted to explain the variance. There is no significant difference in the results after splitting the samples by year. This means that the word set allows for no deletion.

Table 2 lists the keywords on DT extracted from the annual reports of sample companies. All keywords, except for "smart manufacturing", are divided into four categories, namely macro policy, paradigm characteristics, influencing scope, and technology or equipment. It should be noted that the purpose is not to accurately classify these keywords but to identify the relevance among the chosen keywords on DT. The intensity of DT is measured by counting the word frequency of DT keywords in an annual report and dividing the frequency by the total number of words in the annual report. In order to avoid too large a regression coefficient resulting from the excessively small variable value and to visualize the results, the values are all normalized.

Table 2. Keywords on DT in the annual reports.

Category	Keywords
Seed word	smart manufacturing
Macro policy	Made in China 2025, Industry 4.0, Internet+
Paradigm characteristics	Automation, automatic control, informatization, management informatization, informatized management, informatized application, digitization, networking, integration, intelligence, virtualization
Influencing scope	Smart logistics, smart grid, energy Internet, smart energy, smart city, smart service, smart transportation, intelligent transportation, e-government, smart medicine, smart community, smart terminal, smart home
Technology or equipment	Internet of Things, artificial intelligence, cloud computing, big data, cloud services, internet, 3D printing, mobile Internet, biometrics, cloud technology, data center, data analysis, data mining, interconnection, pattern recognition, neural network, mass data, data storage, cloud platform, virtual reality, robots, industrial robots, CNC machine tools, CNC systems, sensors

Note: The keywords above are translated from Chinese by two professional Chinese-English translators.

As there is a time lag in the impact of DT on organizational performance, a time window is chosen as the lag phase. Brynjolfsson and Hitt [11] found that IT often has a strong impact on organizational performance in 2 to 3 years after its introduction. As DT affects operational and financial performance differently, the lag phase for operating performance is set as 1 year, and that for financial performance as 3 years. The sample periods of the independent variables are 2010–2019 and 2010–2017, respectively. Robustness testing would be made to other lag phases.

3.2.3. Control Variables

Firm performance is subjected to the impact of many factors, and some commonly used control variables are included in the analysis. Factors related to company characteristics are controlled, such as size, age, asset-liability ratio, and asset turnover rate. The size and age of a company affect its operations and decision-making. Although their effects on firm performance are controversial, they have long been used as control variables in the research [42]. The *size* of a company is measured by the natural logarithm of its total assets at the end of the fiscal year. Company *age* refers to the years from its listing to the year when statistical analysis is made (logarithm). Solvency has been recognized as influential on firm performance [78], and represented by the *asset-liability ratio* (i.e., the ratio of total liabilities to total assets) in this research. *Asset turnover rate* reflects the utilization efficiency of corporate assets and is measured by dividing operating revenues by the average amount of total assets at the beginning and those at the end of a term. When the dependent variable is financial performance, the *operating costs* (i.e., dividing the sum of operating costs and sales expenses with the operating revenues) are controlled.

Corporate governance is in close relation to organizational behavior and performance. Factors related to corporate governance, including *equity concentration* and *board size*, are controlled as well. The former reflects the company's shareholding structure and is measured by the proportion of shares held by the top ten shareholders, while the latter refers to the number of members of a company's board of directors. As digital foundations vary significantly across industries [22,23], the *digital maturity of an industry* is taken as a control variable as well, denoted by the average value of the intensity of the DT of all companies in the industry. Dummy variables of year and industry are controlled as well.

4. Results

4.1. Main Effects

Tables 3 and 4 list the descriptive statistics and correlation matrices. The mean value of the core explanatory variable "DT intensity" in this research is only 0.020, with much room for improvement. However, there is a large gap between the maximum and minimum values of the digital maturity of industries, with significantly large standard deviations. The data reflects the differences in the digitalization process across different industries. The correlation coefficients between performance and most of the control variables are significant, verifying the appropriate selection of variables to a certain extent. To prevent potential multicollinearity among independent variables, the variance inflation factors (VIF) are checked. The VIF of all variables is below 6, indicating no multicollinearity.

Table 3. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Financial performance	12,821	0.039	0.102	−6.714	0.686
Operating performance	17,233	0.197	0.153	−5.950	0.981
DT	17,295	0.020	0.045	0.000	1.000
Asset turnover ratio	17,262	0.682	0.425	0.005	6.875
Asset-liability ratio	17,130	0.407	0.337	0.008	31.467
Firm size (ln)	17,294	21.884	1.203	17.019	27.468
Firm age	17,295	8.596	6.966	1.000	29.000
Equity concentration	16,973	0.589	0.156	0.046	1.000
Board size	17,252	7.516	3.004	5.000	17.000
Operating cost	17,233	0.804	0.152	0.019	6.950
Industry digital maturity	17,295	7.662	7.571	0.116	47.208

Table 4. Correlation coefficient matrix.

Variable	1	2	3	4	5	6	7	8	9	10
1. Financial performance	1.000									
2. Operating performance	0.181 ***	1.000								
3. DT	0.001	0.078 ***	1.000							
4. Asset turnover ratio	0.085 ***	−0.265 ***	−0.088 ***	1.000						
5. Asset-liability ratio	−0.169 ***	−0.374 ***	−0.054 ***	0.159 ***	1.000					
6. Firm size	−0.002 ***	−0.144 ***	0.029 ***	0.141 ***	0.388 ***	1.000				
7. Firm age	−0.086 ***	−0.224 ***	−0.084 ***	0.110 ***	0.400 ***	0.367 ***	1.000			
8. Equity concentration	0.108 ***	−0.139 ***	0.022	0.066 ***	−0.206 ***	0.079 **	−0.465 ***	1.000		
9. Board size	−0.006	−0.071 ***	−0.087 ***	0.073 ***	0.157 ***	0.267 ***	0.143 ***	−0.025 ***	1.000	
10. Industry digital maturity	0.006 ***	0.074 ***	0.481 ***	−0.165 ***	−0.071 ***	−0.028 ***	−0.092 ***	0.021 *	−0.153 ***	1.000

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

Hausman's test suggests that the firm fixed-effect model should be adopted. Table 5 shows the regression results of DT on the two dimensions of firm performance. Model 1 is the regression of control variables on operating performance. The primary item of DT is introduced to Model 2. The coefficient between DT and operating performance is found to be positive (β = 0.020), with a significance at the 1% level ($p < 0.01$). This indicates that DT is in a significantly positive correlation with operating performance, verifying H1.

Table 5. Regression results of the effects of DT on firm performance.

Variable	Operating Performance		Financial Performance		
	Model 1	Model 2	Model 3	Model 4	Model 5
DT		0.020 ***		−0.028 **	−0.072 ***
		(3.78)		(−2.01)	(−3.05)
DT^2					0.106 ***
					(3.23)
Asset turnover ratio	−0.066 ***	−0.066 ***	0.035 ***	0.035 ***	0.035 ***
	(−19.83)	(−19.91)	(13.08)	(13.13)	(13.13)
Asset-liability ratio	−0.180 ***	−0.180 ***	−0.063 ***	0.001 *	−0.063 ***
	(−21.36)	(−21.42)	(−9.12)	(1.65)	(−9.15)
Firm size	0.002	0.002	0.004 ***	0.004 ***	0.004 ***
	(1.50)	(1.31)	(4.38)	(4.54)	(4.59)
Firm age	−0.031 ***	−0.030 ***	−0.006	0.132 ***	−0.007
	(−8.01)	(−7.92)	(−1.32)	(5.94)	(−1.45)
Equity concentration	0.045 ***	0.046 ***	0.021 **	−0.006	0.021 **
	(4.89)	(5.03)	(2.15)	(−1.40)	(2.12)
Board size	0.000	0.000	0.001 *	0.021 **	0.001
	(0.54)	(0.54)	(1.72)	(2.12)	(1.59)
Operating cost			−0.132 ***	−0.000 **	−0.133 ***
			(−5.90)	(−2.33)	(−5.94)
Industry digital maturity	−0.000	−0.000	−0.001 ***	−0.063 ***	−0.000 *
	(−0.20)	(−1.38)	(−3.34)	(−9.22)	(−1.79)
Constant	0.265 ***	0.269 ***	0.045 *	−0.089 ***	0.043
	(10.40)	(10.50)	(1.72)	(−4.68)	(1.64)
Firm fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Observations	15,268	15,268	10,896	10,896	10,896
Adjusted R^2	0.234	0.235	0.0986	0.0986	0.0989

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

Model 3 is the regression of control variables on financial performance. The primary item of DT is introduced to Model 4, with a significantly negative regression coefficient (β = −0.028, $p < 0.05$). The result shows that DT has a negative linear impact on firm financial performance. As H2 assumes that there is a U-shaped relationship between DT and financial performance, the quadratic term of DT is further introduced to Model 5 to test the expected relationship. The quadratic coefficient is significantly positive (β = 0.106) at the 1% level ($p < 0.01$), and the explanatory power (R^2) of Model 5 is higher than that of Model 4.

Although the result meets the basic conditions of the U-shaped relationship, further verification is made with "Utest" developed by Lin and Mehlum [79], as recommended by Haans et al. [80]. The null hypothesis of "Utest" is that the relationship is monotone or inverse U shape. Alternatively, it is a U shape. To reject the null hypothesis, a three-step procedure is required. First, the coefficient of the quadratic term needs to be positively significant. Second, the slope must be sufficiently steep at both the lower bound (i.e., negative and significant) and upper bound (i.e., positive and significant) of the data range (i.e., DT in this research). Third, the turning point is located within the data range. The first condition is well met as discussed above. Untabulated results show that the slope of the curve at the lower bound of DT is −0.054 and significant at the 5% level, while the slope at the upper bound is 0.136 and significant at the 1% level. In addition, the turning point of DT equals 0.284, falling within the value range (0–1) as shown in the descriptive statistics. The overall test of the non-existence of a U-shaped relationship yields a t-value of 2.29 with an associated *p*-value of 0.011, indicating a rejection of the null hypothesis at a significance level of 5%. The finding further confirms the U-shaped relationship between DT and financial performance. H2 is thus verified.

4.2. Additional Analysis

4.2.1. Long-Term Effects

The payback period is the focus of the decision-making on DT [53]. In traditional IT valuation research, the lag phase of the impact of IT investment (or use) on organizational performance is a controversial topic [11,41,81]. As mentioned in Section 3.2.2, the DT variables in the main effects lag behind operating performance and financial performance by one year and three years, respectively. A lag phase of one to five years is adopted to examine the changes in the effects.

The main results of the long-term effects of DT are shown in Table 6. The regression coefficient of DT on operating performance has always been significantly positive, meaning that DT continues to promote operations within five years after its launch. As for the relationship between DT and financial performance: in the first year, the primary coefficient of DT is significantly negative ($\beta = -0.037$, $p < 0.05$), but the quadratic term is not significant; and the quadratic coefficient has been significantly positive ($p < 0.05$) since the second year, and the significance plummeted ($p < 0.1$) since the fourth year. The coefficient was not significant at all in the fifth year. This means that DT undermines financial performance in the first year after its launch, and the U-shaped effects first appear in the second year. However, the effects disappear in the fifth year.

Table 6. Long-term effects of DT on firm performance.

Dependent Variable	Operating Performance	Financial Performance
DT_{t-1}	0.020 (3.78) ***	−0.037 (−2.19) **
DT_{t-1}^2		0.032 (1.16)
DT_{t-2}	0.047 (2.77) ***	−0.080 (−2.81) ***
DT_{t-2}^2		0.096 (2.20) **
DT_{t-3}	0.034 (1.68) *	−0.072 (−3.05) ***
DT_{t-3}^2		0.106 (3.23) ***
DT_{t-4}	0.044 (1.82) *	−0.036 (−1.09)
DT_{t-4}^2		0.071 (1.90) *
DT_{t-5}	0.066 (2.16) **	0.003 (0.08)
DT_{t-5}^2		0.038 (0.94)

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

4.2.2. Analysis of Heterogeneity

Period Heterogeneity

In view of the impact of government regulation on firm behavior, the differences in the performance outcomes of corporate DT under varied policies are further explored. China introduced the "Made in China 2025" strategy in 2015, taking smart manufacturing as the main direction. Later, more national policies that promote the digitalization of manufacturing have been released (the Chinese government issued the Smart Manufacturing Development Plan (2016–2020) in 2016, the Guidelines on Deepening the "Internet + Advanced Manufacturing" and Facilitating the Development of the Industrial Internet in 2017, and the Action Plan on Industrial Internet Innovation and Development (2021–2023) in 2020). The year 2015 is a watershed in China's strategic arrangement of the DT in the manufacturing industry. This paper divides the study period into two periods: from 2010 to 2014 and from 2015 to 2020. The aim is to examine the impact of DT on firm performance under different policies.

The regression results of the two periods are shown in Table 7. The coefficient of the impact of DT on operating performance is always significantly positive, but the coefficient in the second stage (β = 0.016) is significantly smaller than that in the first stage (β = 0.173). A further inter-group test (Chi2) shows that the difference in coefficients between the two groups is significant at the 1% level. This means that DT generates a less positive impact on business operations under favorable macroeconomic policies. According to the quadratic coefficient and its significance level (β = 0.159, $p < 0.01$), the U-shaped relationship between DT and corporate financial performance did not appear until the second period. During the period from 2010 to 2014, there is no statistical correlation between DT and financial performance.

Table 7. Subsamples by period.

Dependent Variable	Operating Performance		Financial Performance	
	2010–2014	2015–2020	2010–2014	2015–2020
DT	0.173 (6.86) ***	0.016 (3.09) ***	−0.010 (0.36)	−0.110 (−3.30) ***
DT^2			0.037 (0.98)	0.159 (3.05) ***
Controls	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	6074	9194	6037	4859
Adjusted R^2	0.233	0.234	0.183	0.081
Coefficient difference	Chi2 = 103.79 ***		Chi2 = 76.98 ***	

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

Industry Heterogeneity

DT is driven by digital innovation [3,29]. With a solid foundation in R&D, the high-tech industry has stronger digital capabilities [22]. This research divides the samples into high-tech and low-tech industries, aiming to further examine the impact of DT on firm performance. According to the classification of high-tech manufacturing by the National Bureau of Statistics of China, chemical raw materials (C26), pharmaceuticals (C27), chemical fibers (C28), metal products (C34), flexible equipment (C35), dedicated equipment (C36), transportation equipment (C37), electrical machinery (C38), electronic equipment (C39), and instruments and apparatuses (C40) are viewed as high-tech industries, with the rest being low-tech industries.

The regression results of different industries are listed in Table 8. The coefficient of the impact of DT on operating performance is significantly positive in both high-tech and low-tech industries, but the coefficient in the former (β = 0.109) is much smaller than that in the latter (β = 0.285). According to Chi2, the difference between the coefficients is significant at the level of 1%. Therefore, in the high-tech industry, the effects of DT on the improvement of operating performance are much weaker. However, this result is not found in the regression of financial performance. On the contrary, the U-shaped relationship between DT and financial performance exists in high-tech industries only (quadratic coefficient β = 0.121, $p < 0.01$). In low-tech industries, there is no statistically significant relationship between them.

Table 8. Subsamples by industry type.

Dependent Variable	Operating Performance		Financial Performance	
	High-tech industry	Low-tech industry	High-tech industry	Low-tech industry
DT	0.109 (4.19) ***	0.285 (2.88) ***	−0.236 (−3.15) ***	0.051 (0.17)
DT^2			0.121 (3.56) ***	−0.356 (−0.89)
Controls	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	10609	4659	7571	3325
Adjusted R^2	0.209	0.268	0.087	0.166
Coefficient difference	Chi2 = 156.42 ***		Chi2 = 55.19 ***	

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

The dependent variable is measured by substitution to verify the robustness of the results. Specifically, in the measurement of operating performance, only the business cost is taken into consideration. The sales expenses are no longer deducted, i.e., 1-operating cost/operating income. As the sample companies are all listed, earning per share (EPS) instead of ROA is used to measure the financial performance. After the variables are replaced, no substantial change is found in all the regression results above.

5. Discussion

Although IT valuation research once experienced the "productivity paradox" controversy, it confirms that digital technology investment (or use) does help improve organizational performance after the performance measurement approaches and lag phases are adjusted [11–14,38]. However, the DT of companies is more about organizational and strategic transformation than about technologies [1,32]. DT is much more complex in terms of benefits and costs than digital technology investment (or use). This leads to uncertain organizational performance outcomes. This paper makes a fine-grained analysis of the benefits and costs of firm DT from the perspectives of operating performance and financial performance, and then explores the effects of DT on organizational performance in these perspectives. Both hypotheses of this research are verified. DT plays a catalytic role in the process's cost-oriented operating performance. However, for profitability-based financial performance, this role does not come into play after the intensity of transformation reaches a certain threshold (0.284 in the sample of this research); before that, the costs of transformation will undermine the financial performance.

The analysis of the benefits and costs of DT in different dimensions of organizational performance contributes to the research on the outcomes of organizational performance resulting from DT. Existing literature on DT and organizational performance remain at the exploratory stage, yielding mixed findings. On the one hand, the link between DT and various organizational performance variables (e.g., innovation performance, financial performance, firm growth, and market performance) [4] is mostly found in industrial surveys, and the results vary along with samples. More importantly, such research lacks a sound theoretical basis. On the other hand, most academic research focuses on the impact of specific digital technologies on organizations [24–28]. DT today is more about the joint effect of multiple digital innovations at the organizational level than about the adoption of a single digital technology [1,3,29]. From the "benefit-cost" rationale, this paper looks into the potential benefits (improving operations vs. stimulating growth) and accompanying costs (digital investment vs. coordinated integration) of DT at the organizational level. As far as the author knows, this paper is one of the first studies that clarifies the benefits and costs of DT in different performance dimensions. In addition, by extracting the keywords in the annual reports of companies, the paper describes the intensity of DT, providing valuable references for the quantitative study on the DT of firms.

We find that the benefits of DT to main business processes outweigh the digital operation investment required. In the context of organizational transformation, this finding confirms a long-held view in the IS field, i.e., IT directly optimizes the operation process [13,15]. As for the profitability of an enterprise, DT stimulates business innovation and growth on one hand and brings about high integration costs on the other [16,20]. The positive effect does not show up until the transformation reaches a certain intensity. The curve relationship between DT and ROA helps explain that DT does not necessarily lead to net financial benefits, because there are costs in it. However, as transformation deepens, it will yield sufficient financial benefits to compensate for the costs. Our results provide empirical evidence for the pros and cons of DT toward financial consequences [9,21], suggesting intensity is the key to implementing DT.

In some sense, the U-shaped relationship reconciles the controversy on whether DT improves or undermines firm financial performance in existing literature [21,23,53]. Our finding is in alignment with the argument of Deng et al. [68], in which the economic value of digital technologies could hardly become visible until companies radically transform themselves to succeed in the digital world. According to a report by Deloitte on China's manufacturing industry in 2018, only 4% of the surveyed companies are at the deep application stage of Industry 4.0 (Data sources from the official website of Deloitte China: https://www2.deloitte.com/cn/zh/pages/energy-and-resources/articles/china-smart-manufacturing-report-2018.html (accessed on: 18 November 2021)). Based on the data of China's manufacturing companies from 2010 to 2017, this paper shows that the inflection point of the relationship between the intensity of DT and ROA is about 0.284, and 5% of the surveyed companies are on the right of the inflection point in 2017. This means that only a small number of companies in China's manufacturing industry are able to make profits from DT. The finding echoes the results of Deloitte's field survey.

By examining long-term effects and environmental heterogeneity, we further specify the boundary conditions on the organizational performance effects of DT. The impact of DT on operational processes is more lasting (five years at least) than on profitability. This finding confirms that the sustainable impact of digital technologies on firm performance on one hand [26,41,81], and reveals the difference in the impact between operating performance and financial performance on the other. In addition, the results of heterogeneity analysis show that DT improves business operations regardless of policy shocks or industry changes. However, its effect weakened after the "Made in China 2025" (in 2015) was proposed and in the high-tech industries. At the same time, the impact of DT on financial performance only shows up after 2015 or in high-tech industries. In the period with favorable policies or the industries with strong (digital) innovation capabilities, the subjective willingness and objective conditions for DT are stronger and sounder. The effects of DT are supposed to be more satisfactory. Therefore, it is assumed that the U-shaped relationship between DT and profitability does not show up without relatively favorable conditions. However, under "favorable conditions", the effects of DT on operations have weakened. A possible explanation is that the digital maturity and operational efficiency of Chinese manufacturing companies have witnessed significant improvement after 2015. DT can do less to bring about significant improvement to operations. Similarly, the effects of DT on business operations weaken in the high-tech industries as well.

The findings of this research have important practical implications. To begin with, although DT in the manufacturing sector requires high fixed expenditures [9], it is positively correlated with operating performance. This means that DT does help improve operational efficiency, which will facilitate the managers and policymakers to decide to promote DT. However, the U-shaped relationship between DT and profitability prompts companies to make a cautious evaluation of existing resource endowments, expected profits, and transformation costs, thereby choosing appropriate strategies to reach the "break-even point" of DT. At the same time, the long-term performance effects of DT provide a reference on the payback period of digital investment. According to the Accenture survey, 85% of the companies surveyed hope to see the return on investment in DT within one year [53]. This research finds that, after one year since the launch of DT, it improves operations significantly, but drags down profitability. If a company expects a return in the form of profit, it needs to wait for two to four years. Moreover, if a company lacks a solid digital foundation, DT helps improve its operating processes by a large margin, but the marginal utility may decline. If a company launches DT in pursuit of profits, it needs to leverage supporting conditions, including favorable government policies and its innovation capabilities.

6. Conclusions

Although the performance outcomes of DT are the core concern of companies in the digital age, relevant research is still under-explored. Based on a fine-grained analysis of the "benefit-cost" of DT, this paper examines the relationship between DT and business operating and financial performance. The hypotheses are tested based on the second-hand data of 2254 Chinese manufacturing companies, with panel regression analysis being made. The results show that DT elevates the process-oriented operating performance and is in a U-shaped relationship with the profit-based financial performance. We also find that the impact of DT on the operating performance is more lasting than on the financial performance. The conditions required by the operating performance are more easing as well. To sum up, it is easier for firms to improve the operation process than to make profits through DT.

Nonetheless, there are limitations to this research. First of all, research made based on secondary data could only look at some characteristics of complex phenomena, such as DT in this paper. On the one hand, some critical digital actions are never disclosed in firms' annual reports; on the other, although the words in annual reports reflect some key information of DT at the organizational level, their validity needs further verification. Future research is suggested to study DT from different dimensions: design questionnaires that include a series of questions so as to obtain sufficient primary data; and explore the joint effects of different dimensions of DT on organizational performance from a configurational perspective (e.g., qualitative comparative analysis). In addition, this research is made based on the manufacturing data of China. There are wide differences in the digitization foundations, willingness, and external conditions across different countries and industries [9,22,23]. To make the findings widely applicable, more empirical tests need to be made based on the samples from more countries and industries.

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