Establishing a Big Data Driver for Digital Transformation, Supplier Concentration and Total Factor Productivity in Enterprises

Hua Zhang[1], Xinyan Gao[2], Hengrui Chen[1], Zhongxi Lu[3], Hongji Yang[3]*

[1] *Sunwah International Business School, Liaoning University, China*
[2] *The Bartlett Centre for Advanced Spatial Analysis, University College London, UK*
[3] *School of Computing and Mathematical Sciences, Leicester University, UK*
huazhang@lnu.edu.cn, ucfnaoc@ucl.ac.uk, 20216602224@smail.lnu.edu.cn,
zl258@leicester.ac.uk, hongji.yang@leicester.ac.uk

Abstract

Nowadays, various industries are increasingly investing in constructing big data platforms to achieve digitalisation. Digitalisation has become a critical factor in improving the efficiency and effectiveness of enterprises. This paper explores the influence of digital transformation (DIT) on corporate total factor productivity (TFP). Based on data from publicly listed enterprises in China from 2007 to 2022, this paper demonstrates that DIT significantly improves their TFP. Supplier concentration partially mediates the relationship between DIT and TFP. Furthermore, the enterprise life cycle moderates the impact of DIT on TFP. Specifically, during the growth stage, the influence of DIT on TFP is not significant. During the maturity and decline stages, DIT positively affects the TFP. The impact of DIT on TFP is particularly pronounced in enterprises in western China, as well as in large and high-tech enterprises. The paper examines whether, how and when DIT affect TFP. The findings contribute novel evidence that strategic DIT enable enterprise to improve TFP through decreased supplier concentration. For both scholars and practitioners, this research provides valuable insights into how digital transformation can pay dividends by improving overall productivity.

Keywords: Corporate total factor productivity, Digital transformation, Enterprise life cycle, Supplier concentration

1 Introduction

Corporate TFP is a crucial indicator for analysing the status of economic development. The enhancement of corporate TFP has profound strategic significance for China in achieving high-quality economic development. Since the reform and opening up in 1978, China has undergone flying economic growth by relying on substantial inputs of labour, capital, land, and other production factors. Some scholars in Western countries have mentioned that Chinese economic growth is driven by resource inputs rather than efficiency improvement, indicating that this investment-led approach is not sustainable in the long run [1]. It is a matter of fact that the traditional demographic dividends and labour cost advantages in China are diminishing. It is no longer sustainable to rely on the production factor-driven development model. Hence, how to improve production efficiency is attracting increasing concerns.

Digital technologies, involving the Internet of Things (IoT) [2], cloud computing [3], artificial intelligence (AI), and big data constantly integrating into enterprise production and operations, provide a new engine for the improvement of corporate TFP. It is of significance to expedite the development of a modernised economic system, concentrate on enhancing TFP, and drive the economy to attain qualitative advancement and quantitative growth. In light of this situation, it is crucial to explore whether DIT can act as a catalyst for enhancing the development of TFP in enterprises. If so, what are the paths and mechanisms of DIT influencing TFP? Does enterprise digitalisation have varying effects on TFP at different stages of the life cycle? Studying the above questions is beneficial for accurately evaluating the impact of enterprise digitalisation at the micro level and gaining a deeper understanding of the significance of digitalisation for efficiency reform.

In practice, DIT seems to significantly promote enterprise productivity. However, in theory, the literature on the relationship between DIT and TFP is still in its early stages. Scholars have acknowledged that DIT improves TFP through the mediators of technological innovation [4], resource allocation [5], innovation capability [6], financial constraints [7-8], and R&D capital and human capital [9-10], while there is a lack of research on the impact mechanism of DIT on TFP based on supply chain management. In response to this situation, this paper collects data from Chinese quoted enterprises. The study empirically examines the impact mechanism of DIT on TFP based on supply chain management. It has been found that DIT significantly improves firm TFP. Supplier concentration partially mediates the relationship. The enterprise life cycle positively moderates the relationship. Specifically, during the growth stage, the contribution of DIT to TFP is insufficient. During the mature and decline stages, DIT efficiently improves TFP. Furthermore, the effect of DIT on overall productivity is more prominent in Chinese western, large, and high-tech enterprises.

This paper offers three main contributions. Firstly, it

*Corresponding Author: Xinyan Gao; E-mail: ucfnaoc@ucl.ac.uk
DOI: 10.53106/160792642024052503014

discusses the impact of firm digitalisation on TFP from the perspectives of resource allocation, financing constraints, R&D and human capital, etc. In contrast to previous literature, this paper explores the mechanism based on supply chain management. Secondly, building on the confirmation of the above mechanism, this paper discusses the variations in the impact of DIT on TFP at different stages of the enterprise life cycle. This study expands the research scope on the relationship between enterprise digitalisation and TFP and provides guidance for enterprise innovation practices. Thirdly, this paper contributes to understanding the heterogeneous effects of digitalisation on TFP based on various characteristics.

2 Theoretical Background and Hypothesis Development

2.1 Digital Transformation and TFP

TFP is a measure of corporate efficiency in using various production factors to create products and services within a specific time [5]. TFP simultaneously takes all production factors into account, including not only the physical factors (such as labour, capital, natural resources, etc.), but also the non-physical factors (such as technological progress, innovation, and management, etc.) [11]. An improvement in TFP means that an enterprise or even a country obtains more outputs with the same inputs of production factors. Digital transformation refers to the integration of the digital technologies with the real economy to promote upgrading of traditional industries [12]. Schumpeter's innovation theory suggests that the introduction of new combinations of factors into the production system can effectively improve enterprise efficiency. Along with digitalisation of enterprises, data, as a new factor of production, is continuously integrated into the production system, forming the foundation for increased TFP [13]. Specifically, first, in the process of enterprise digitalisation, digital technologies can be rapidly used to acquire, analyse and utilise data to timely and comprehensively analyse consumer demand. Concurrently, new technologies and methods are being discovered and applied to provide digital products and services to expand the scope of business, which ultimately helping enterprises create new revenue. Second, by adopting digital transformation, enterprises can enhance their production processes and reduce costs through automation and intelligent systems, which not only minimises manual operations and errors but also significantly boosts productivity. Third, enterprises undergoing digital transformation can raise their management and decision-making abilities through data analysis and intelligent decision-making, which, in turn, increase their TFP. Accordingly, this paper proposes the following hypothesis:

H1: DIT positively affects TFP.

2.2 Mediating Role of Supplier Concentration

Based on Porter's theory of industrial competition, the bargaining power of suppliers is a significant factor that influences an enterprise's competitive position [14]. Due to unbalanced supply and demand, their bargaining power diminishes when there are just one or a very small number of suppliers in the supplier market. In this case, switching to a new supplier is costly and there is a cartel relationship between the supplier and the enterprise. Suppliers monopolise pricing decisions. Digital transformation can mitigate the disadvantage of having too few suppliers and reduce supplier concentration, thereby increasing the TFP of the firm. Firstly, with the realisation of digitalisaiton, the introduction of digital technologies and applications strengthens communication and shortens negotiation time between enterprises and suppliers [15], prompting enterprise to choose suppliers more flexibly [16]. Besides, enterprises can automate procurement orders, expedite supplier selection, and implement efficient inventory management practices. This helps to reduce procurement lead time and establish flexible supplier-customer relationships with various suppliers. Hence, supplier concentration will decrease [17]. Secondly, digital transformation facilitates information sharing and transparency. Transmitting comprehensive information to different people in different geographical locations is faster and cheaper [17]. The rapid flow of information leads to greater transparency in procurement prices, and enterprises can choose suppliers more diversified. Through controlling the risk caused by information imbalance and price monopoly, digital transformation decreases the concentration of enterprise suppliers.

Furthermore, the TFP of an enterprise can continue to increase as supplier concentration decreases. To be specific, initially, with the increase of the number of suppliers that enterprises can choose, the procurement channels of enterprises are increased, and the bargaining power is increased, which directly leads to a reduction in the cost of production inputs and an increase in the TFP of the enterprise. Subsequently, it is normal for higher supplier concentration to increase the business risks of enterprises, such as the risk of sudden interruptions or shortage of material and service supply, the risk of adverse contract terms revision, and the difficulty of changing suppliers [18]. In this case, enterprises will hold more cash in custody to deal with potential risks, which may reduce the likelihood that firms will invest more in innovative products and services. Hence, it is not conducive to the improvement of corporate TFP. On the contrary, with the decrease of supplier concentration, the cost of cash custody and production risk are reduced, and enterprises are more likely to use funds for innovative products and services, which, in turn, will improve corporate TFP. Accordingly, this paper proposes:

H2: Supplier concentration plays a mediating role in the mechanism of DIT influencing TFP.

2.3 Moderating Effect of Enterprise Life Cycle

Enterprises at different stages of their life cycle have distinct positions in terms of financial operations, organisational structure, and market development. Therefore, the degree of digitalisation has a different effect on TFP [19]. First, during the growth stage, enterprises lack stable supply chains, and dynamic knowledge of potential customers, costs, and industries. During this stage, although both the number of products and sales volume increase sharply, they face fierce market competition, large financing needs and less financing channels [20]. In addition, enterprises in the growth stage are faced with more investment opportunities, so they must put limited funds towards the development of new products and new markets to achieve expansion goals [21]. Therefore, when enterprises undergo digital transformation, they are limited by the resource acquisition ability and financing constraints. The influence of corporate digitalisation on TFP may not be significant.

During the mature stage, enterprises have a complete supply chain, fixed customer base, and stable cash flow. The investment in market expansion decreases, so they have sufficient capital and conditions for digital transformation. At this stage, based on their strong resource base, their organisational structure is increasingly perfect, and their operational risks are relatively reduced, providing investors with good trust [20]. As a result, firms face fewer financing constraints and diversified financing options, making it easier to turn the benefits of digital transformation for efficiency advantages. Moreover, by introducing digital technologies and applications, enterprises in the mature stage can use differentiation strategy to form competitive advantages that are difficult for competitors to imitate, and ultimately improve the TFP of enterprises. Therefore, in the mature stage, the higher the level of DIT, the more it contributes to enterprise's TFP.

During the recession stage, the market share and profit margin of enterprises gradually decline, the financial situation deteriorates day by day, and creditors and investors lose confidence in enterprises [22]. The business focus of enterprises shifts from external to internal, and they attempt to manipulate external financial reports purposefully by means of earnings management to achieve the purpose of whitening the situation [23]. Therefore, enterprises in the recession stage hope to undergo digital transformation to improve TFP and promote themselves into a new life cycle. Based on the above analysis, this paper proposes:

H3: The enterprise life cycle moderates the relationship between DIT and TFP. The contribution of DIT to enterprise TFP is insufficient in the growth stage, DIT positively affects TFP in the maturity and decline stages.

The theoretical framework is shown in Figure 1.

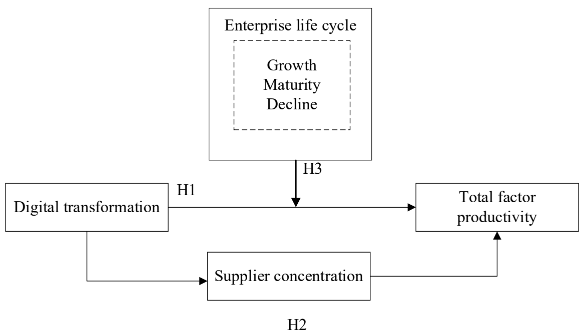

Figure 1. The theoretical framework model

3 Methodology

3.1 Sample Selection and Data Sources

This paper selects Chinese listed companies as the research samples. Since the widespread use of digital tools emerged after 2006 [24], this paper sets the time range of research as 2007 to 2022. The data sources include CSMAR database, Wind database, and CNINF database. To ensure the research quality, the samples were screened as follows: (1) excluding the financial industry; (2) eliminating ST or ST* listed enterprises; (3) removing samples with significant missing data; (4) winsorising the core variables at 1% and 99%. Finally, 19,366 observations were collected.

3.2 Variable Measurement

(1) Explained variable: total factor productivity (TFP). Referring to Lu and Lian [25], this paper uses the LP method to measure TFP. The business revenue, net fixed assets, cash paid for products and services and the number of employees to respectively measure the total output, capital input, intermediate input and labor input were used in this study. In addition, this paper also tests the robustness of the TFP calculated by OLS, FE and GMM methods.

(2) Explanatory variable: digital transformation (DIT). Referring to Wu et al. [12], this paper conducts word frequency statistics and text analysis to measure DIT. Specifically, it is divided into AI technology, blockchain technology, cloud computing technology, big data technology and digital technology application to construct a digital dictionary. The word frequency statistics are carried out, and the total word frequency is processed by taking the logarithm of +1.

(3) Mediating variable: supplier concentration (SUC). According to the research of Li et al. [26] and Chen and Liu [27], we measure SUC by calculating the proportion of the sum of the purchase amount from the top five suppliers to the total purchase amount.

(4) Moderating variable: enterprise life cycle (Lifec). Referring to Cao et al. [28], this paper uses three indicators, including net cash flow from operating activities, investing activities and financing activities. For example, companies are considered to be in the maturity stage when their net cash flow from operating activities, investing activities and financing activities are positive, negative and negative, respectively.

(5) Control variables: This paper controls enterprise Age (Age), asset-liability ratio (Lev), net profit rate of total assets (ROA), ownership concentration (Top5) and nature of enterprise ownership (SOE), gross profit (Gross), invest-return ratio (Invest). Time and industry dummy variables are fixed.

3.3 Model Construction

This paper sets the baseline model (Formula 1):

$$TFP_{i,t} = \beta_0 + \beta_1 DIT_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t}. \quad \textbf{(1)}$$

Where i and t respectively denote the enterprise and year, β denotes the estimated parameter, C represents the control variables, *Year* and *Industry* denote year and industry fixed effects, respectively, and Ɛ denotes the error term.

Table 1. Measurements of the variables

Type	Symbol	Variable descriptions
Dependent variable	TFP	Total outputs divided by total inputs
Independent variable	DIT	The keyword frequency statistics; Log-transformed
Control variables	Age	Year of observation minus the year of the company's foundation; log-transformed
	Lev	Total liabilities divided by total assets
	ROA	Net profit divided by total assets
	TOP5	The number of shares held by the top 5 shareholders divided by the total number of shares.
	SOE	1 for state-owned enterprises, and 0 for others
	Gross	The difference between operating revenues and costs divided by operating revenues
	Invest	The cash paid to construct fixed assets, intangible assets, and other long-term assets divided by the total assets.

4 Empirical Analysis

4.1 Descriptive Statistics

As shown in Table 2, the mean of TFP is 8.316, and the median is 8.215, pointing that data distribution are approximately normal. The standard deviation (SD) is 0.990, with a minimum value of 6.295 and a maximum value of 11.168. It indicates significant differences in TFP among different companies. The average of enterprises' DIT is 1.535, and the median is 1.386, demonstrating that the distribution pattern is skewed to the right. The SD is 1.450, with a minimum value of 0.000 and a maximum value of 5.209. The overall level of DIT among Chinese enterprises is low. Finally, the descriptive statistics of other variables are consistent with other studies.

Table 2. Results of descriptive statistics

Variables	Observation	Mean	SD	Minimum	Median	Maximum
TFP	19366	8.316	0.990	6.295	8.215	11.168
DIT	19366	1.535	1.450	0.000	1.386	5.209
SUC	19366	0.053	0.080	0.001	0.023	0.462
Lifec	19366	1.773	0.757	1.000	2.000	3.000
Age	19366	2.916	0.321	1.946	2.944	3.555
ROA	19366	0.039	0.068	-0.246	0.039	0.230
TOP5	19366	52.057	14.580	21.005	51.934	85.392
SOE	19366	0.268	0.443	0.000	0.000	1.000
Gross	19366	0.294	0.175	-0.003	0.261	0.825
Invest	19366	0.061	0.064	0.000	0.040	0.340

4.2 Baseline Regression

As shown in Table 3, Column (1) presents the baseline regression results without controls. Column (2) presents the regression results after adding year and industry fixed effects. Column (3) presents the regression results after including both control variables and the fixed effects. The results are robust that DIT is positively related to TFP. In Column (3), for every 1 unit increase in DIT, the TFP increases by 0.122 units. H1 is supported.

Table 3. Baseline regression results

	(1) TFP	(2) TFP	(3) TFP
DIT	0.093^{***}	0.108^{***}	0.122^{***}
	(19.013)	(19.026)	(24.602)
Age			0.069^{***}
			(3.347)
ROA			4.965^{***}
			(42.677)
TOP5			0.005^{***}
			(10.675)
SOE			0.369^{***}
			(24.241)
Gross			-2.277^{***}
			(-51.610)
Invest			-0.599^{***}
			(-6.142)
Industry & Year FE	N	Y	Y
_cons	8.173^{***}	8.150^{***}	8.099^{***}
	(829.288)	(765.350)	(120.918)
N	19366	19366	19366
adj. R^2	0.019	0.151	0.350

t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.3 Endogeneity Test

Despite the significant results of the baseline regression, three theoretical endogeneity problems exist: self-selection bias, omitted variable problem, and reverse causality problem. Therefore, we address the endogeneity problem using the following methods:

4.3.1 Heckman Test

Further, Heckman test is used to explore the impact of DIT on TFP. In the first stage of the equation, "whether the enterprise carries out digital transformation" is utilised as the explanatory variable. If the level of digitalisation in the enterprise surpasses the median degree of digitalisation in the industry for the current year, the enterprise has undergone digital transformation, which is recorded as 1. Conversely, if it does not exceed the median digitalisation degree, it is recorded as 0. At the same time, with reference to the research methodology of Nie et al. [29], it is included the average degree of digital transformation of other listed companies in their industry as a variable in the probit regression model, along with the control variables, to obtain the Inverse Mills Ratio (IMR). In the second stage, the IMR estimated is included in the new regression model. As shown in Table 4, column (2) shows that the coefficient of the relationship between DIT and TFP is still significantly positive after the addition of IMR, which indicates that firms' DIT enhances their TFP, and the conclusion of this study remains robust.

Table 4. Heckman test results

	(1) TFP
DIT	0.122***
	(11.366)
Age	0.001
	(0.024)
ROA	5.075***
	(28.061)
TOP5	0.005***
	(4.680)
SOE	0.328***
	(8.066)
Gross	-2.259***
	(-22.302)
Invest	-0.855***
	(-4.450)
IMR	0.453***
	(3.073)
Industry & Year FE	Y
_cons	7.043***
	(21.708)
N	19343
adj. R^2	0.350

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3.2 Instrumental Variable Method

The instrumental variable (IV) method is also employed to assess the impact of DIT on TFP. The average level of digital transformation among other enterprises in the same province in the current year is used as the IV for the digital transformation level of the enterprise in the same year, meeting the criteria of correlation and exogeneity. According to Li et al.'s research [30], there is a significant industry peer effect on enterprise digital transformation. This means that the DIT of other enterprises in the same industry can significantly promote the DIT of a specific enterprise. However, it is challenging for enterprises at the same digital level within the industry to directly impact their own TFP. In Table 5, column (1) shows that the coefficient of IV is significantly positive; Column (2) shows that the coefficient of DIT is significantly positive. It indicates that after alleviating the endogeneity problem, the result is still valid.

Table 5. Instrumental variable method

	(1) TFP	(2) TFP
DIT	0.378***	0.161***
	(18.810)	(4.463)
Age	-0.258	0.078***
	-8.050	(3.285)
ROA	0.096	4.985***
	0.650	(49.984)
TOP5	-0.001	0.004***
	-1.750	(8.966)
SOE	-0.155	0.385***
	-7.080	(23.851)
Gross	0.048	-2.272***
	0.830	(-57.409)
Invest	-1.250	-0.548***
	-8.51	(-5.108)
Industry & Year FE	Y	Y
_cons	1.026	7.840***
	(1.210)	(13.640)
N	18240	18240
adj. R^2	0.342	0.338

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4 Robustness Test

4.4.1 Changing Measurement Method of TFP

The impact of DIT on TFP may be affected by the measurement error of corporate TFP. For this reason, this paper re-measures the TFP and re-validates the influences of DIT on corporate TFP by using the methods of OLS, FE and GMM instead of the method of LP. Columns (1-3) of Table 6 show that the results of this study are still valid when the variable measurement method of TFP is replaced.

Table 6. Robustness test

	(1) TFP_OLS	(2) TFP_FE	(3) TFP_GMM	(4) TFP
DIT	0.118***	0.122***	0.080***	0.277***
	(19.642)	(19.377)	(19.661)	(21.366)
Age	0.129***	0.144***	-0.048***	0.064***
	(5.128)	(5.435)	(-2.898)	(3.095)
ROA	5.220***	5.334***	4.010***	4.955***
	(39.461)	(38.652)	(39.997)	(42.467)
TOP5	0.005***	0.006***	0.002***	0.004***
	(10.225)	(10.181)	(6.315)	(10.278)
SOE	0.550***	0.594***	0.007	0.361***
	(29.357)	(30.037)	(0.559)	(23.566)
Gross	-2.659***	-2.754***	-1.496***	-2.275***
	(-51.609)	(-51.048)	(-40.915)	(-51.556)
Invest	0.339***	0.533***	-2.190***	-0.645***
	(2.830)	(4.206)	(-28.162)	(-6.590)
Industry & Year FE	Y	Y	Y	Y
_cons	10.281***	10.805***	3.799***	8.189***
	(127.099)	(126.602)	(68.702)	(122.073)
N	19366	19366	19366	19366
adj. R^2	0.320	0.313	0.402	0.344

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4.2 Narrowing Sample Research Interval

China's real enterprises have accelerated their integration with new technologies such as the Internet, big data, cloud computing and artificial intelligence, promoting their digital transformation. Therefore, the sample interval has been shortened to 2013-2021 to re-verify the impact of DIT on enterprises' TFP. Column (4) of Table 6 shows that the results of this study are still valid after the sample interval is narrowed.

5 Mechanism Analysis

5.1 Mediating Mechanism of Supplier Concentration

Models (2) and (3) are established to verify the mediating effect of supplier concentration:

$$SUC_{i,t} = \beta_0 + \beta_1 DIT_{i,t} + \beta_n C_{i,t} + Year_{i,t} + Industry_{i,t} + \varepsilon_{i,t}. \quad \textbf{(2)}$$

$$TFP_{i,t} = \beta_0 + \beta_1 DIT_{i,t} + \beta_2 SUC_{i,t} + \beta_n C_{i,t} + Year_{i,t} + Industry_{i,t} + \varepsilon_{i,t}. \quad \textbf{(3)}$$

Where SUC represents supplier concentration. Other indicators are the same as Formula (1).

As shown in Table 7, in Column (1), DIT negatively affects supplier concentration, with a coefficient of -0.006, significant at the level of 1%. In column (2), supplier concentration negatively affects TFP, with a coefficient of -0.585, significant at the level of 1%. Besides, the coefficient on DIT decreases (compared with 0.122 in Column (3) of Table 2). As such, supplier concentration plays a partial mediating role. H2 is supported.

Table 7. Analysis of mechanism effect

	(1) SUC	(2) TFP	(3) TFP	(4) TFP	(5) TFP
DIT	-0.006***	0.119***	0.123***	0.098***	0.114***
	(-13.999)	(23.782)	(19.714)	(16.774)	(21.562)
SUC		-0.585***			
		(-6.941)			
Growth			0.133***		
			(7.794)		
Growth×DCG			-0.008		
			(-1.027)		
Mature				0.101***	
				(7.347)	
Mature×DCG				0.055***	
				(8.562)	
Decline					-0.307***
					(-13.621)
Decline×DCG					0.037***
					(3.651)
Age	-0.003	0.068***	0.075***	0.065***	0.072***
	(-1.225)	(3.277)	(3.650)	(3.161)	(3.512)
ROA	0.021**	4.977***	5.023***	4.896***	4.867***
	(1.997)	(42.624)	(42.983)	(42.008)	(42.058)
TOP5	-0.000	0.005***	0.005***	0.005***	0.004***
	(-0.112)	(10.701)	(11.222)	(10.671)	(10.474)
SOE	-0.005***	0.367***	0.373***	0.368***	0.366***
	(-3.284)	(24.093)	(24.492)	(24.206)	(24.199)
Gross	-0.031***	-2.295***	-2.249***	-2.277***	-2.277***
	(-7.087)	(-51.847)	(-50.907)	(-51.656)	(-51.846)
Invest	-0.010	-0.605***	-0.922***	-0.659***	-0.920***
	(-1.068)	(-6.232)	(-8.951)	(-6.565)	(-9.311)
Industry & Year FE	Y	Y	Y	Y	Y
_cons	0.081***	8.146***	8.024***	8.079***	8.181***
	(11.604)	(121.238)	(119.036)	(120.568)	(122.203)
N	19366	19366	19366	19366	19366
adj. R^2	0.056	0.352	0.353	0.353	0.359

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Regulating Mechanism of Enterprise Life Cycle

Model (4) is established to verify the moderating effect of enterprise life cycle:

$$TFP_{i,t} = \beta_0 + \beta_1 DIT_{i,t} + \beta_2 Lifec_{i,t} + \beta_3 DIT_{i,t} \times Lifec_{i,t} + \beta_n C_{i,t} + Year_{i,t} + Industry_{i,t} + \varepsilon_{i,t} \quad \textbf{(4)}$$

Where *Lifec* represents corporate life cycle. Other indicators are the same as Formula (1).

As shown in Columns (3)-(5), the coefficient of Growth×DCG is -0.008, not significant, the coefficient of Mature×DCG is is 0.055, significant, and the coefficient of Decline×DCG is 0.037, significant. As such, enterprise life cycle moderates the relationship between DIT and TFP. Specifically, the contribution of DIT to enterprise TFP is insufficient in the growth period, and it has a significantly positive effect on TFP in the maturity period and decline period, which supports H3.

5.3 Heterogeneity Analysis

The impact of DIT on TFP probably varies across regions. China has 31 provincial-level administrative regions except Hong Kong, Macao and Taiwan, which can be divided into eastern, western and central regions based on the level of economic development. Western regions are economically underdeveloped areas, while eastern and central regions are economically developed areas. As is shown in Column (1-3) of Table 8, the effect of DIT on corporate TFP is more prominent in Chinese western enterprises. Besides, the effectiveness of DIT practices is influenced by the size of the organisation. This paper categorises the sample into large enterprise group (total assets are more than the sample average) and small and medium-sized enterprise (SMEs) (total assets are less than the sample average). As is shown in Column (4-5) of Table 8, The effect of DIT on corporate total factor production is more prominent in the large companies. Moreover, the effectiveness of DIT practices may be influenced by the technological level of the firms. This study divides the sample into high-tech and non-high-tech enterprises, the results of Column (6-7) of Table 7 show that the effect is more prominent in high-tech enterprises.

Table 8. Heterogeneity analysis results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	TFP	TFP	TFP	TFP	TFP	TFP	TFP
	East	Mid	West	SMEs	Large	Non-tech	High-tech
DIT	0.123***	0.112***	0.137***	0.060***	0.067***	0.064***	0.095***
	(21.729)	(9.040)	(7.372)	(7.354)	(10.397)	(9.187)	(12.027)
Age	-0.022	0.429***	0.258***	0.842***	0.590***	0.793***	0.727***
	(-0.925)	(8.573)	(3.478)	(7.627)	(5.981)	(8.541)	(7.059)
ROA	4.873***	5.031***	5.169***	2.891***	1.963***	2.416***	2.719***
	(37.296)	(16.141)	(11.835)	(20.514)	(15.736)	(19.135)	(19.037)
TOP5	0.003***	0.007***	0.008***	0.002*	-0.001	0.003***	0.004***
	(6.375)	(7.326)	(5.823)	(1.907)	(-0.783)	(3.112)	(3.887)
SOE	0.399***	0.309***	0.447***	-0.118***	-0.054	-0.020	-0.025
	(20.107)	(9.428)	(10.293)	(-2.978)	(-1.573)	(-0.607)	(-0.631)
Gross	-2.443***	-2.130***	-1.464***	-1.155***	-0.528***	-1.146***	-0.720***
	(-46.970)	(-20.717)	(-9.182)	(-9.440)	(-5.390)	(-10.885)	(-6.555)
Invest	-0.653***	-0.579***	0.353	0.055	0.146*	0.193**	0.313***
	(-5.608)	(-2.714)	(1.122)	(0.490)	(1.769)	(2.036)	(3.043)
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y
_cons	8.493***	6.912***	6.840***	6.559***	6.102***	5.916***	6.074***
	(110.275)	(43.119)	(28.532)	(19.148)	(20.021)	(20.972)	(19.032)
N	13935	3358	1837	8329	10154	8746	10007
adj. R^2	0.360	0.389	0.334	0.875	0.794	0.869	0.884

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusions and Implications

The processing and analysis of big data are becoming the cornerstone of the new generation of information technology integration applications. Big data serves as the new engine for sustained and rapid growth of the information industry. Decision-making in all sectors is shifting from being "business-driven" to "data-driven". Various organisations are increasingly investing in constructing big data platforms to achieve digital transformation to improve overall productivity. Digital transformation is crucial for the survival and development of enterprises. Based on listed enterprise data in China from 2007 to 2022, this paper explores the impact of DIT on TFP. The findings indicate that DIT can enhance corporate TFP, with supplier concentration partially mediating the relationship. The impact of DIT on TFP varies significantly depending on the stage of enterprise life cycle. During the growth stage, DIT's contribution to TFP is insufficient. During the maturity and decline stages, DIT positively influences TFP. The findings of this paper have practical implications for managers seeking to implement digitalisation, enhance efficiency, and foster high-quality economic development.

Firstly, new technologies, new products, new services, and new business formats for the big data market will continue to emerge. Enterprises should enhance the management capabilities of their supply chain systems during the digital transformation process. This will enable them to achieve cost control, efficiency improvement, and innovation through collaboration with upstream enterprises. Before enterprises decide to embark on digital transformation, they need to conduct a comprehensive assessment and engage in systematic planning of their resources and capacity reserves, aligning them with their development goals and stages. Based on a realistic assessment of resources and capabilities, enterprises can leverage digital technology to decrease supplier concentration by promoting digital infrastructure and developing digital capabilities. This can help expand the value reserves of enterprises by encompassing related subjects. Simultaneously, supplier enterprises can utilise complementary resources and capabilities to continuously innovate the combination of resources and capabilities, expand the resource pool, and enhance production efficiency.

Secondly, the implementation of digital transformation in various enterprises should involve tailored actions based on their individual development situations. Enterprises in the growth stage, should especially focus on the long-term planning of the digital strategy and address resource shortages by building fundamental digital capabilities. Additionally, they should avoid head-on market confrontation with large enterprises, and achieve the competitive advantage brought by the popularisation of digital capabilities in niche markets through surprising methods. For mature and declining enterprises, the primary focus is on promoting the redevelopment of traditional resources and capabilities through digital transformation. Particular attention should be given to integrating digital strategies with the benefits of current market and technology. Enterprises can specifically use digital technologies to increase the value of their current products and services. This creates strong digital connections between the existing products and services, making it harder for consumers to switch and solidifying the enterprise's dominant position in the market.

Acknowledgement

Project source- Liaoning Social Science Planning Foundation (L23CGL005).

References

[1] H. J. Yu, Digital Transformation and Enterprise Total Factor Productivity, *Management and Administration*, pp. 1-14, June, 2023. DOI: 10.16517/j.cnki.cn12-1034/f.20230619.001

[2] D. Singhal, L. Ahuja, A. Seth, An Insight into Combating Security Attacks for Smart Grid, *International Journal of Performability Engineering*, Vol. 18, No. 7, pp. 512-520, July, 2022.

[3] S. Jhingran, M. K. Goyal, N. Rakesh, DQLC: A Novel Algorithm to Enhance Performance of Applications in Cloud Environment, *International Journal of Performability Engineering*, Vol. 19, No. 12, pp. 771-778, December, 2023.

[4] N. Li, X. H. Wang, Z. R. Wang, X. Y. Luan, The impact of digital transformation on corporate total factor productivity, *Frontiers In Psychology*, Vol. 13, pp. 1-13, December, 2022.

[5] X. G. Huang, B. S. Hou, S. J. Ye, Y. S. Li, Research on the Relationship between Digital Transformation and Total Factor Productivity of Enterprises – Inspection Based on the Perspective of Resource Allocation, *Price: Theory and Practice*, No. 11, pp. 107-111, November, 2022.

[6] Z. C. Ren, Z. H. Zhao, The Impact of Digital Transformation on Total Factor Productivity Improvement in Manufacturing- Micro Evidence From Listed Companies, *Industrial Technology and Economy*, Vol. 41, No. 11, pp. 23-30, November, 2022.

[7] Y. R. Cheng, X. R. Zhou, Y. J. Li, The effect of digital transformation on real economy enterprises' total factor productivity, *International Review of Economics & Finance*, Vol. 85, pp. 488-501, May, 2023.

[8] Y. Wu, H. H. Li, R. Y. Luo, Y. B. Yu, How digital transformation helps enterprises achieve high-quality development? Empirical evidence from Chinese listed companies, *European Journal of Innovation Management*, Early Access, pp. 1-12. April, 2023. https://doi.org/10.1108/ejim-11-2022-0610

[9] S. G. Li, Y. X. Tian, How Does Digital Transformation Affect Total Factor Productivity: Firm-Level Evidence from China, *Sustainability*, Vol. 15, No. 12, Article No. 9575, June, 2023.

[10] H. F. Guo, H. M. Wang, Digital Transformation and Service Industry Total Factor Productivity, *Modern Economic Exploration*, No. 6, pp. 92-102+113, June, 2022. DOI: 10.13891/j.cnki.mer.2022.06.013

[11] F. Guo, S. G. Yang, H. Jin, The Influence of Digital Economy on Enterprise Total Factor Productivity and its Mechanism, *Modern Finance and Economics- Journal of Tianjin University of Finance and Economics*, Vol. 42, No. 9, pp. 20-36, September, 2022. DOI: 10.19559/j.cnki.12-1387.2022.09.003

[12] F. Wu, H. Z. Hu, H. Y. Lin, X. Y. Ren, Enterprise Digital Transformation and Capital Market Performance - Empirical Evidence from Stock Liquidity, *Management World*, Vol. 37, No. 7, pp. 130-144+10, July, 2021. DOI: 10.19744/j.cnki.11-1235/f.2021.0097

[13] M. Keklik, *Schumpeter, Innovation and Growth: Long-Cycle Dynamics in the Post-WWII American Manufacturing Industries*, *Taylor and Francis*, 2018.

[14] M. E. Porter, How competitive forces shape strategy, *Harvard Business Review*, Vol. 67, No. 2, pp. 137-145, March-April, 1979.

[15] M. Obal, R. A. Lancioni, Maximizing buyer-supplier relationships in the digital era: Concept and research agenda, *Industrial Marketing Management*, Vol. 42, No. 6, pp. 851-854, August, 2013.

[16] I. M. Cavalcante, E. M. Frazzon, F. A. Forcellini, D. Ivanov, A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing, *International Journal of Information*

Management, Vol. 49, pp. 86-97, December, 2019.
[17] S. Mohapatra, IT and Porter's competitive forces model and strategies, in: Y. Dwivedi, M. Wade, S. Schneberger (Eds.), *Information Systems Theory: Explaining and predicting our digital society*, *Integrated Series in Information Systems*, Vol. 28, Springer, New York, NY, 2012, pp. 265-281.
[18] X. D. Zhang, M. F. Zou, W. M. Liu, Y. F. Zhang, Does a firm's supplier concentration affect its cash holding? *Economic Modelling*, Vol. 90, pp. 527-535, August, 2020.
[19] X. H. Wang, M. L. Zhao, S. P. Zhang, L. Cheng, Corporate Strategic Radicality, Digital Transformation, and ESG Performance: Moderating Effect of Corporate Life Cycle Stage, *Soft Science*, Vol. 38, No. 3, pp. 77-84, March, 2024. DOI: 10.13956/j.ss.1001-8409.2024.03.11
[20] M. M. Hasan, A. Habib, Corporate life cycle, organizational financial resources and corporate social responsibility, *Journal of Contemporary Accounting & Economics*, Vol. 13, No. 1, pp. 20-36, April, 2017.
[21] L. L. Gu, Y. Peng, The Impact of Corporate Philanthropy on Firm Performance:The Moderating Effect of Corporate Life Cycle Stage, *Management Review*, Vol. 34, No. 3, pp. 243-254, March, 2022.
[22] D. L. Zhang, S. S. Xu, F. Xue, H. C. Wang, Corporate Strategy and Social Responsibility Performance -Based on the Perspective of Resource Acquisition, *China Soft Science*, No. 6, pp. 111-123, June, 2022.
[23] J. Sun, B. Q. Wang, F. Cao, X. Q. Liu, Does Corporate Strategy Affect Earnings Management? *Management World*, No. 3, pp. 160-169, March, 2016.
[24] Q. Li, L. G. Liu, J. B. Shao, The Effects of Digital Transformation and Supply Chain Integration on Firm Performance - The Moderating Role of Entrepreneurship, *Economic Management*, Vol. 43, No. 10, pp. 5-23, October, 2021.
[25] X. D. Lu, Y. J. Lian, Estimation of Total Factor Productivity of Industrial Enterprises in China: 1999-2007, *China Economic Quarterly*, Vol. 11, No. 2, pp. 541-558, January, 2012. DOI: 10.13821/j.cnki.ceq.2012.02.013
[26] W. Li, L. H. Chen, Y. Y. Chi, Supplier/Customer Concentration and Corporate Green Innovation, *Soft Science*, Vol. 37, No. 3, pp. 97-102+126, March, 2023.
[27] X. C. Chen, X. Liu, Supplier (Customer) Concentration and Company Information Disclosure Violation, *Nankai Management Review*, Vol. 24, No. 6, pp. 213-224, December, 2021.
[28] Y. Cao, X. H. Chen, F. Q. Wang, An empirical comparative study of life cycle classification methods of listed companies in China, *Journal of Systems and Management*, Vol. 19, No. 3, pp. 313-322, June, 2010.
[29] X. K. Nie, W. H. Wang, X. Pei, Does Enterprise Digital Transformation Affect Accounting Comparability? *Accounting Research*, No. 5, pp. 17-39, May, 2022.
[30] Q. Li, S. H. Wang, P. D. Deng, K. Y. Wang, The Peer Effect of Enterprise Digital Transformation, *Science & Technology Progress and Policy*, Vol. 40, No. 17, pp. 1-12, September, 2023. DOI: 10.6049/kjjbydc.2022040319

Biographies

Hua Zhang received her MSc degree in Project and Enterprise Management from London University and PhD degree in Business School from Liaoning University. She is a lecturer of Sunwah International Business School of Liaoning University. She has published 10 papers in SSCI, SCI, and EI indexed journals.

Xinyan Gao is currently studying for her MSc in Spatial Data Science at University College London, specializing in GIS, machine learning, and urban systems analytics. Holding a first-class Mathematics degree from Xi'an Jiaotong-Liverpool University, her research spans data science, mathematical modeling, and statistical analysis.

Hengrui Chen studies in Liaoning University's Sunwah International Business School and is currently a junior majoring in Business Management. Her entrepreneurial project won the first prize at the national level. Two papers have been indexed by CNKI national journals. She has participated in provincial and municipal projects.

Zhongxi Lu, in her third PhD year at the University of Leicester, is studying enhancing creativity through aesthetics, after being awarded with an MPhil focused on emotion's role in creativity. She is working as a graduate teaching assistant at currently university. Shi has published in IEEE conferences.

Hongji Yang is a Professor in the School of Computing and Mathematical Sciences, Leicester University, UK. His research interests include software engineering, creative computing and internetworking. He became an IEEE Golden Core Member in 2010.