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Diversification Strategies and Digital Transformation: Evidence from Chinese-Listed Enterprises

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Abstract: This study investigates the empirical relationship between diversification strategies—specifically geographic and product diversification—and enterprise digital transformation. Utilizing a sample of Chinese publicly listed companies from 2009 to 2021, along with comprehensive analyses and tests, the study finds that greater geographic and product diversification significantly promote enterprise digital transformation. Additionally, a heterogeneity analysis reveals that state ownership does not influence geographic diversification but does impact product diversification. Conversely, executives' overseas experience affects geographic diversification but not product diversification. Furthermore, the geographical location of firms emerges as a potential factor influencing digital transformation. These findings enhance the understanding of factors that drive enterprise digital transformation, offering both theoretical and empirical insights into the feasibility of digital transformation through the lens of diversification strategies. The results also provide practical insights for companies in the planning or implementation stages of digital transformation.

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Introduction

In the rapidly evolving digital landscape, companies must continuously adapt to sustain a competitive edge. Digital transformation encompasses the fundamental and accelerated restructuring of business activities, organizational processes, capabilities, and models to harness the opportunities presented by the digital era (Gong & Ribiere, 2021). This transformation extends beyond simply digitizing workflows and processes; it involves a profound shift in core practices, organizational processes, culture, and mindset, with a strategic focus on delivering enhanced value to customers, employees, and society. Consequently, digital transformation has garnered significant attention among information systems (IS) researchers and practitioners (Legner et al., 2017; Markus & Rowe, 2021; Mergel, Edelmann, & Haug, 2019; Vial, 2019).

In line with this growing interest, numerous companies have already embarked on digital transformation initiatives, with reported outcomes becoming increasingly available. Findings from a McKinsey & Company survey on the performance of digital transformation efforts suggest that digital technologies have the most substantial impact on enhancing organisational members' experiences by improving their work methods. Following this, key outcomes include cost reduction and revenue growth achieved through optimising existing processes, although revenue generation from entirely new business models has proven more limited than anticipated (Digital Initiative Group, 2021). Digital transformation not only yields economic benefits but also enhances productivity, fosters specialisation, refines business models, and strengthens competitive advantages, thus supporting overall enterprise performance (Abou-foul, Ruiz-Alba, & Soares, 2021; Pan et al., 2022; Ritter & Pedersen, 2020; Yuan et al., 2021). Nevertheless, the proportion of companies achieving comprehensive digital transformation remains relatively low. According to the Accenture report on Chinese enterprises' digital transformation in 2021, the percentage of Chinese companies reaching this milestone rose from 11% in 2020 to 16% in 2021. Despite this progress, many companies have yet to engage in digital transformation, particularly within the broader scope of the global digital economy's evolution. Consequently, examining strategies to effectively promote corporate digital transformation has become increasingly essential.

The existing literature on facilitators of enterprise digital transformation largely centres on internal and external factors. Internally, key enablers include human capital, organisational culture, and technological capital, encompassing elements such as management characteristics, employee competencies, organisational learning, internal governance, and resource allocation, as well as technology acquisition, adoption, and investment (Cai et al., 2024; Eller et al., 2020; Kraus et al., 2021; Zhang, Xu, & Ma, 2022, 2023; Zhou, Wang, & Lan, 2023; Zhu, Li, & Ma, 2024). Externally, the focus is primarily on the institutional and market environment. Institutional factors comprise policies that directly or indirectly support low-carbon environmental initiatives and government tax incentives (Chen, 2023; Chen, Xiao, & Jiang, 2023). The market environment, on the other hand, includes regional digital infrastructure, business climate, and industry competition (Luo et al., 2023; Verhoef et al., 2021; Wu et al., 2023).

This study seeks to examine the potential impact of enterprise diversification strategies on promoting digital transformation, an area not extensively explored in prior research. The focus on diversification strategies is informed by the substantial body of work highlighting the critical role of diversification in various business activities (Hitt, Hoskisson, & Ireland, 1994; Hitt, Hoskisson, & Kim, 1997; Jacquemin & Berry, 1979). Historically, diversification has been viewed as a strategy for mitigating risk and seizing new growth opportunities through market expansion or product development, which may lead to transformations in both the internal and external structures of an enterprise, as well as fostering innovation (Orlando et al., 2018). Given this, we hypothesize that diversification strategies may significantly contribute to driving digital transformation within organizations.

Diversification typically involves entering new markets or industries, which may expose companies to geographic limitations, as well as diverse technologies and business practices (Wiersema & Bowen, 2008). In response to these challenges and to maintain competitiveness and efficiency, companies may accelerate the adoption of digital tools and processes. Such diversification often necessitates innovation to differentiate within new markets, and this innovation increasingly takes a digital form, including the integration of new software, platforms, and technologies that are key drivers of digital transformation (Hinings, Gegenhuber, & Greenwood, 2018). Managing a diversified product portfolio requires streamlined, integrated operations, which can be facilitated by digital tools and platforms that automate processes, improve communication, and offer real-time data analytics (Gillani et al., 2024). Furthermore, to stay competitive across multiple markets, companies must leverage digital technologies to enhance product offerings, services, and customer experiences (Kraus et al., 2021). As a result, companies are adopting advanced digital solutions. In conclusion, diversification strategies can act as a catalyst for digital transformation by compelling organizations to adopt innovative digital technologies, optimize operations, and remain competitive in diverse markets (Kane et al., 2015).

This paper investigates the relationship between enterprise diversification strategies and digital transformation, specifically assessing whether a diversification strategy facilitates an enterprise's digital transformation. Drawing on a review of relevant theoretical frameworks and empirical evidence, the study empirically examines the influence of diversification strategies on digital transformation. The findings aim to enhance the understanding of strategic management in the context of digital transformation and offer valuable insights for both scholars and practitioners.

Literature Review and Hypothesis

Literature Review

Enterprise Digital Transformation

The factors driving enterprise digital transformation can be broadly categorized into internal and external aspects. Internal factors include human capital, organizational culture, and technological capital. Within human capital, key influences on digital transformation stem from CEOs with IT backgrounds (Cai et al., 2024), senior managers (Zhang & Bu, 2024), and CEO overconfidence (Zhu et al., 2024). Employee skills (Eller et al., 2020) and employees' perceptions of digital transformation also play critical roles in this process (António Porfírio, Augusto Felício, & Carrilho, 2024). However, the age of the CEO is negatively correlated with digital transformation, often due to concerns over personal reputation (Zou et al., 2024).

Organizational culture factors include the optimization of organizational structure (Zhang & Wang, 2024), the implementation of effective internal supervision mechanisms (Zhang, Lu, & Wang, 2024), organizational digital learning (Sousa & Rocha, 2019), equity distribution and incentives (Zhou et al., 2023), and leadership (AlNuaimi et al., 2022). Technological capital involves the introduction and acquisition of technology (Kraus et al., 2021), with investments in information technology (IT) and core technological changes serving as significant drivers of digital transformation (Zhang et al., 2023).

External factors, particularly institutional and market forces, play a significant role in driving digital transformation within enterprises. Institutional factors, such as environmental regulations, tax policies, and credit incentives, can motivate enterprises to adopt digital transformation by addressing capital and labour mismatches and promoting sustainable development (Chen, 2023; Guo, Xiao, & Guo, 2023). Market forces, which include environmental support and industry competition, further enhance this motivation. The development of network infrastructure and digital finance has strengthened the incentives for businesses to undertake digital transformation (Chen, 2023). Regional advancements in digital infrastructure offer strategic, resource-based, and capability-driven advantages that facilitate the digital transformation of enterprises (Wu et al., 2023). Moreover, companies operating in highly competitive industries are more likely to pursue digital transformation to maintain their market position (Verhoef et al., 2021). A favourable business environment, coupled with industry competition and market uncertainty, significantly influences decision-making related to digital transformation (Luo et al., 2023).

Diversification Strategies and Enterprise Activities

Diversification refers to a strategic approach where an enterprise operates simultaneously in multiple product or service markets. This strategy is crucial for companies seeking to establish a presence across various markets and leverage a range of resources (Hitt et al., 1997). As such, diversification plays a pivotal role in several aspects of an enterprise's operations. It helps mitigate operational risks, reduce capital costs, and shield companies from market volatility (Amit & Livnat, 1989; Hann, Ogneva, & Ozbas, 2013; Wang, Shen, & Ngai, 2023a). By broadening their product lines and entering new markets, companies can cater to diverse customer needs, strengthen brand influence, expand market share, and enhance profitability (Jacquemin & Berry, 1979; Kim, Hoskisson, & Lee, 2015). Additionally, diversification strategies enable resource acquisition and organizational learning, fostering innovation and cross-border collaboration. These strategies improve resource utilization across industries, providing a competitive edge (Barney et al., 2011; Gao & Chou, 2015; Oh, 2023). Thus, diversification strategies not only assist in risk management and generating economic benefits but also drive sustainable innovation and the development of competitive advantages.

Since the concept of diversification was introduced, both geographical and product diversification have become key areas of focus in strategic management research (Bolli & Woerter, 2013; Garrido-Prada, Delgado-Rodriguez, & Romero-Jordán, 2019; Juergensen, Narula, & Surdu, 2022). Geographical diversification refers to the expansion into new geographic regions or markets across various global locations and countries (Hitt et al., 1997). In contrast, product diversification involves entering new product markets that the enterprise has not previously operated in Hitt et al. (1997). Despite the distinct nature of these two diversification strategies, both have the potential to significantly expand an enterprise's knowledge base and resource pool (Xie, Wang, & Miao, 2021).

The impact of geographical and product diversification on enterprise innovation and performance is framed by theories such as the resource-based view, transaction cost economics, and organizational learning (Chang & Wang, 2007; Hitt et al., 1997; Tang, Wu, & Zhu, 2020). These strategies enhance performance through synergies, capacity building, and cost complementarities (Hitt et al., 1997; Hitt et al., 2006; Teece, 2014). Geographical diversification promotes innovative learning by providing access to diverse resources (Christofi et al., 2019), while product diversification enables cross-industry knowledge integration to support sustainable innovation (Chang & Wang, 2007). As digital transformation is a key aspect of innovation (Damanpour, 1991), this study explores the relationship between diversification and digital transformation, an area with limited research.

Hypothesis

Drawing on existing academic research on diversification strategies and digital transformation, we argue that the unique resources gained through geographical and product diversification play a significant role in driving enterprise digital transformation. This argument is supported by several key considerations. Firstly, the resource-based view suggests that digital transformation, as an innovative process, is effectively driven by an enterprise's distinct resources (Civelek, Krajčík, & Ključnikov, 2023; Clemente-Almendros, Nicoara-Popescu, & Pastor-Sanz, 2024). Both geographical and product diversification can promote investments in digital technologies and foster a higher tolerance for failure, which in turn facilitates a deeper level of digital transformation (Hitt et al., 1997; Luo et al., 2023). Enterprises operating across diverse industry markets gain access to a broader range of resources from various industry partners (Hitt et al., 1997; Wu, Chen, & Jiao, 2016). The valuable resources and capabilities embedded within organisations, business networks, industries, and societies act as strategic assets that either initiate or accelerate digital transformation (Gong & Ribiere, 2021). Moreover, complementary assets, innovative ideas, market insights, and technical support drawn from multiple markets can be leveraged to advance an enterprise's digital transformation (Hitt et al., 1997; Li & Geng, 2012).

From an organisational learning perspective, knowledge gained from specialisation and international exposure plays a crucial role in overcoming barriers and driving digital transformation (Clemente-Almendros et al., 2024). Geographical and product diversification provide enterprises with opportunities to acquire new insights from a diverse range of customers, competitors, and partners across various industries (Hitt et al., 1997; Salomon & Jin, 2010; Zahra, Ireland, & Hitt, 2000). By operating in multiple markets, enterprises enhance their capacity to absorb diverse knowledge and information (Colombo, Piva, & Rossi-Lamastra, 2014; Corradini, Demirel, & Battisti, 2016; Wu et al., 2016). This process enriches the enterprise's knowledge base, facilitating knowledge recombination and idea exchange, which encourages the alteration of existing knowledge, resources, and capabilities, thus supporting transformation and innovation (Wang et al., 2023b). When enterprises leverage the potential of social learning through geographical and product diversification, digital transformation is enabled (Sousa & Rocha, 2019).

From a strategic management perspective, heightened industry competition can drive enterprises to actively pursue digital transformation (Verhoef et al., 2021). Enterprises engaged in geographical and product diversification face increased competitive pressures, which compel them to embrace digital transformation to sustain their competitive advantage (Li & Geng, 2012; Wu et al., 2016). Both internal and external factors, such as the competitive environment and market dynamics resulting from diversification strategies, play a pivotal role in driving digital transformation (Chen, Wang, & Wan, 2021). Furthermore, to address the diverse needs of various clients, the complexities associated with geographical and product diversification spur innovation and the adoption of new business practices (Hitt et al., 1997; Wu et al., 2016). The interactions between enterprises and clients across multiple industries strengthen internal knowledge absorption capabilities, facilitating the integration of technological and strategic components essential for professional development, thus fostering a greater inclination towards digital transformation (Marino-Romero et al., 2022). Based on this analysis, we propose the following hypotheses.

Hypothesis 1: Geographical diversification can promote enterprise digital transformation.

Hypothesis 2: Product diversification can promote enterprise digital transformation.

Research Design

Sample Selection and Data Sources

The article draws on data from A-share companies listed in China between 2009 and 2021. Financial data, ownership details, and other company-related information are sourced from the China Stock Market and Accounting Research (CSMAR) database. Data on geographical and product diversification are obtained from the China Customs database and the WIND Economic database, respectively. Samples with outliers and missing financial data are excluded. Following data collection and pre-processing, the final sample consists of 21,595 annual observations from 2,519 listed companies.

Variable Description

Dependent Variable

Enterprise Digital Transformation: Building on previous research, we assess an enterprise's commitment to digital transformation by analysing the occurrence of keywords related to digital transformation in its annual reports (Wu et al., 2021). A list of these keywords is provided in Appendix Table A1. The degree of digital transformation within an enterprise is quantified based on the frequency of these digital-related terms in the annual reports. To mitigate potential biases in the data, we apply a logarithmic transformation to the word frequencies associated with digital transformation, thereby creating the proxy variable EDT for enterprise digital transformation.

Independent Variable

Geographical Diversification: The academic literature lacks a standardised approach for measuring geographical diversification. However, prior studies have shown that exports effectively capture the characteristics of geographical diversity, particularly in terms of accessing external resources and facilitating learning effects for companies (Cai, Wu, & Zhang, 2020; Salomon & Jin, 2010; Salomon & Shaver, 2005). Consequently, we use the natural logarithm of an enterprise's export volume as a proxy variable (GD) for geographical diversification.

Product Diversification: While various methods exist to measure product diversification, industry-relatedness is the most commonly applied metric (Qian, 2002). Among these, the entropy index of product diversity is frequently utilised (Chang & Wang, 2007; Hitt et al., 1997; Jacquemin & Berry, 1979). By using this index, total product diversification is derived by summing its related and unrelated diversification components (Jacquemin & Berry, 1979). Therefore, we adopt the entropy index as a proxy variable for product diversity (PD).

Control Variable

In addition to the core explanatory variables, this study incorporates relevant control variables at the enterprise level to further improve the accuracy of the research findings. The enterprise-level control variables include firm size (size), firm age (age), board size (board), leverage ratio (lev), employee size (employee), ownership type (soe), and executives' overseas study experience (overseas). Detailed definitions of these variables are provided in Appendix Table A2.

Theory and Methodology

To examine the impact of geographical and product diversification on enterprise digital transformation, we estimated the following regression model.

$$EDT_{\mathrm{it}} = \alpha + \beta GD_{it} + \gamma Controls_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (1)$$

$$EDT_{\mathrm{it}} = \alpha + \beta PD_{it} + \gamma Controls_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

The variable $EDTit$ represents the level of digital transformation of the enterprise i in year t. The independent variable $GDit$ represents the level of geographical diversification of the enterprise i in year t. The independent variable $PDit$ represents the level of product diversification of enterprise i in year t. The variable *Controlit* represents the level of control variables of enterprise i in year t. The research model is shown in Figure 1.

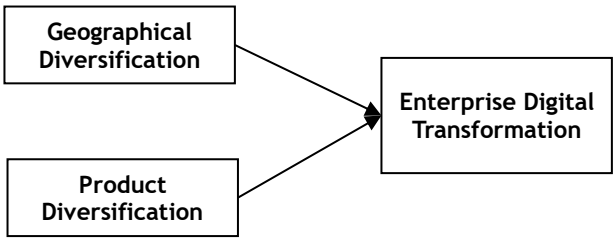

Figure 1: Research Model.

Empirical Result

Descriptive Statistics

Table 1 presents the descriptive statistics for the key variables in this study. The mean and standard deviation of the EDT were 1.473 and 1.403, respectively, suggesting variability in the digital transformation levels across the sample enterprises. The mean and standard deviation of GD were 15.873 and 4.412, respectively, indicating differences in the geographical diversification of the enterprises. The mean and standard deviation of PD were 0.309 and 0.449, respectively, reflecting variation in the product diversification among the sample enterprises.

Table 1: Descriptive Statistics.

Variable	Obs	Max	Mean	Std. Dev.	Min
EDT	20,768	1.473	1.403	**0**	6.306
GD	20,768	15.873	4.421	1.154	25.320
PD	20,768	0.309	0.449	**0**	2.478
Size	20,768	21.762	1.113	18.266	27.967
Age	20,768	2.823	0.349	0.693	4.127
Board	20,768	2.094	0.193	**0**	2.890
Lev	20,768	0.363	0.196	0.010	1.957
Employee	12.29	20,768	7.308	1.130	**0**
Soe	20,768	0.203	0.402	**0**	**1**
Oversea	20,768	0.569	0.495	**0**	**1**

Baseline Regression Result

The regression results are presented in Table 2. In model M1, the regression coefficient for GD is 0.0039, which is significant at the 5% level. In model M2, the regression coefficient for PD is 0.289, significant at the 1% level. In models M3 and M4, additional control variables were included, with regression coefficients of 0.0047 for geographical diversification and 0.12 for product diversification. The significance of geographical diversification was strengthened, while the significance of product diversification remained unchanged, both at the 1% level. These results demonstrate a significant positive relationship between geographical diversification, product diversification, and the digital transformation of enterprises. As both geographical and product diversification increase, the level of digital transformation within enterprises also rises, thereby supporting our hypothesis.

Table 2: Regression Result of Diversification on Enterprise Digital Transformation-Time Individual Fixed Effect Model.

MODEL	(1)	(2)	(3)	(4)
VARIABLES	**EDT**	**EDT**	**EDT**	**EDT**
GD	0.00391**		0.00467***	
	-0.00186		-0.00167	
PD		0.289***		0.120***
		-0.0359		-0.0302
Size			0.315***	0.309***
			-0.0356	-0.0358
Age			1.473***	1.459***
			-0.0908	-0.0908
Board			0.127	0.124
			-0.0905	-0.0903
Lev			-0.189*	-0.199*
			-0.113	-0.113
Employee			0.0231	0.0212
			-0.025	-0.0251
Soe			-0.0716	-0.0757
			-0.0783	-0.0784
Oversea			0.0085	0.0085
			-0.0283	-0.0282
Constant	1.241***	1.219***	-9.964***	-9.742***
	-0.0323	-0.015	-0.619	-0.622
Year	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes
Observations	20,768	20,768	20,768	20,768
R-Squared	0.138	0.149	0.334	0.336

Endogeneity Test

Instrumental Variable Method (IV)

The endogeneity issue in this study may primarily arise from reverse causality between enterprise digital transformation and both geographical and product diversification, as well as potential biases due to omitted variables. To mitigate this, we used lagged two-month geographical diversification and the natural logarithm of the total compensation of the top three executives as instruments for geographical diversification. For product diversification, we employed the number of industries in which the enterprise operates as an instrument, assuming a strong correlation with the level of diversification. The IV regression results are presented in Table 3. Columns 1 and 2 report statistically significant coefficients, confirming the relevance of the instruments. Columns 3 and 4 show the second-stage regression results, where the coefficients for both geographical and product diversification remain positive and statistically significant, thus reaffirming the robustness of our primary findings, even after addressing potential endogeneity concerns.

Table 3: IV Regression Results.

VARIABLES	(1) First GD	(2) Second EDT	(3) First PD	(4) Second EDT
GD		0.0717*		
		-2.57		
PD				0.0971***
				-3.7
L2.GD	-0.0745***			
	-6.57			
Tmtp	0.122*			
	-2.31			
Industry_n			0.434***	
			-93.17	
Size	-0.0941	0.287***	0.0132**	0.310***
	-0.82	-12.87	-3.03	-12.88
Age	-0.61	1.736***	0.0513***	1.461***
	-1.93	-27.38	-4.84	-24.64
Board	-0.331	0.0796	-0.00166	0.124
	-0.98	-1.19	-0.12	-1.77
Lev	1.016**	-0.291***	0.0226	-0.196*
	-2.81	-3.85	-1.56	-2.52
Employee	0.0648	0.0689***	0.00654*	0.0216
	-0.75	-4.03	-2.01	-1.13
Soe	0.0481	-0.0358	0.0205	-0.0754
	-0.18	-0.67	-1.69	-1.29
Oversea	0.122	0.000313	0.00421	0.00872
	-1.17	-0.02	-1.01	-0.41
N	13147	13147	20718	20718

t Statistics in Parentheses
* p<0.05, ** p<0.01, *** p<0.001

Propensity Score Matching (PSM)

Table 4: PSM Regression Results.

VARIABLES	(1) EDT	(1) EDT
GD	0.00507***	
	-0.00166	
PD		0.107***
		-0.0305
Size	0.298***	0.287***
	-0.0403	-0.0413
Age	1.483***	1.478***
	-0.0992	-0.104
Board	0.118	0.053
	-0.0977	-0.105
Lev	-0.216*	-0.163
	-0.121	-0.131
Employee	0.0345	0.0417
	-0.0356	-0.0299
Soe	-0.00773	-0.0149
	-0.0782	-0.0873
Oversea	0.00684	0.0133
	-0.0303	-0.0323
Constant	-9.706***	-9.441***
	-0.679	-0.71
Observations	16,473	13,818
R-Squared	0.328	0.323

Robust Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

To address sample bias and endogeneity, this study applied propensity score matching (PSM). The experimental group included firms with geographical diversification above the median and those with product diversification across two or more industries, while controls had lower diversification. Nearest neighbour matching with a calliper of 0.0001 was performed, and regression was conducted on the matched sample. The results, shown in Table 4, reveal that both geographical diversification (0.0051) and product diversification (0.107) are significantly positively associated with enterprise digital transformation, confirming the robustness of the main findings.

Entropy Balance Matching (EBM)

As an alternative approach, EB matching provides a robust covariate balance and reduces dependence on the Logit model in the initial stage of PSM. Unlike PSM, EB matching retains all observations, avoiding sample loss due to unmatched cases. Regression analysis of the EB-matched sample, shown in Table 5, yields coefficients of 0.0048 for geographical diversification and 0.1 for product diversification, both significant at the 1% level. These results align with those in Table 2, underscoring that even with balanced covariate distributions, geographical and product diversification continue to significantly impact enterprise digital transformation, further affirming the reliability of the findings.

Table 5: EBM Regression Results.

VARIABLES	(1) EDT	(2) EDT
GD	0.00478***	
	-0.00142	
PD		0.1000***
		-0.0243
Size	0.311***	0.302***
	-0.0249	-0.0263
Age	1.431***	1.438***
	-0.0605	-0.0612
Board	0.111	0.142**
	-0.0712	-0.0714
Lev	-0.216***	-0.219***
	-0.0785	-0.0814
Employee	0.0372*	0.0383*
	-0.0198	-0.0218
Soe	-0.0574	-0.0784
	-0.06	-0.0597
Oversea	0.00569	0.0049
	-0.0217	-0.0226
Observations	20,718	20,718
R-Squared	0.89	0.888

Robust Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Supplementary Tests

Robustness Test

Replace the Variable of Enterprise Digital Transformation

Following the digital transformation keyword criteria established by Zhao, Wang, & Li (2021), we use EDT2 as an alternative variable for measuring enterprise digital transformation. This variable incorporates a broader range of digital transformation-related keywords, offering a more comprehensive reflection of various facets of digital transformation. As shown in Table 6, the regression results confirm that both geographical and product diversification significantly and positively impact enterprise digital transformation, further reinforcing the robustness of our initial findings.

Table 6: Regression Results of Substituting Dependent Variables.

VARIABLES	(1) EDT2	(2) EDT2
GD	0.00278**	
	-0.00138	
PD		0.116***
		-0.0262
Size	0.352***	0.357***
	-0.0328	-0.0326
Age	1.275***	1.288***
	-0.073	-0.0729
Board	0.112	0.115
	-0.077	-0.0769
Lev	-0.455***	-0.444***
	-0.0958	-0.0963
Employee	0.0557**	0.0577**
	-0.0265	-0.0267
Soe	-0.120*	-0.117*
	-0.0702	-0.0697
Oversea	-0.0113	-0.0109
	-0.0253	-0.0254
Constant	-8.680***	-8.864***
	-0.56	-0.558
Observations	20,768	20,768
R-Squared	0.403	0.401

Robust Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Reduction of the Sample Period

Following Cai et al. (2024) and others, we tested the robustness of our results by regressing the digital transformation variable over a shortened sample period. This adjustment, covering 2010 to 2019, aimed to reduce the influence of the 2008 financial crisis and the 2020 pandemic on digital transformation. As shown in Table 7, the findings remain consistent with the main regression results, reaffirming that geographical and product diversification positively influence enterprise digital transformation.

Table 7: Regression Results of the Reduced Sample Period.

VARIABLES	(1) EDT	(2) EDT
GD	0.00508**	
	-0.00207	
PD		0.118***
		-0.0389
Size	0.358***	0.349***
	-0.0445	-0.045
Age	1.613***	1.598***
	-0.113	-0.113
Board	0.184*	0.185*
	-0.106	-0.106
Lev	-0.205	-0.209
	-0.137	-0.137
Employee	0.00845	0.00692
	-0.0292	-0.0293
Soe	-0.0948	-0.0961
	-0.106	-0.106
Oversea	0.0205	0.0222
	-0.0333	-0.0333
Constant	-11.31***	-11.01***
	-0.769	-0.782
Observations	16,196	16,196
R-Squared	0.32	0.321

Robust Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Changing the Measurement Method: Tobit Regression

Following Zhu et al. (2024), additional robustness testing was performed using the Tobit model, given that some observations for the EDT1 were zero. We recoded EDT1 as 1 for non-zero values and 0 otherwise, then conducted Tobit regression. Table 8 shows that the coefficients for geographical and product diversification are significant at the 5% and 10% levels, respectively. These results confirm that the main findings

remain robust across different regression methods.

Table 8: Results of Tobit Regression.

	(1)	(2)
VARIABLES	EDT0_1	EDT0_1
GD	0.00175***	
	-0.000615	
PD		0.0150*
		-0.00815
Size	0.0976***	0.0969***
	-0.00629	-0.00629
Age	0.481***	0.478***
	-0.0143	-0.0143
Board	-0.133***	-0.133***
	-0.0226	-0.0226
Lev	-0.117***	-0.118***
	-0.0232	-0.0233
Employee	-0.00753	-0.00755
	-0.00568	-0.00568
Soe	-0.164***	-0.165***
	-0.0142	-0.0142
Oversea	0.0263***	0.0266***
	-0.00729	-0.00729
Constant	-2.434***	-2.388***
	-0.11	-0.109
Sigma_u	0.388***	0.387***
	-0.00616	-0.00615
Sigma_e	0.260***	0.260***
	-0.00137	-0.00137
Observations	20,768	20,768

Further Heterogeneity Tests

SOEs Vs. Non-SOEs

Table 9: Heterogeneity Results of State-Owned Enterprises and Non-State-Owned.

	(1)	(2)	(3)	(4)
	soe_0_EDT	soe_1_EDT	soe_0_EDT	soe_1_EDT
GD	0.00387**	0.00641*		
	-2.08	-1.96		
PD			0.126***	0.0655
			-4.02	-0.86
Size	0.357***	0.248***	0.348***	0.246***
	-8.22	-4.01	-8.01	-3.97
Age	1.496***	1.143***	1.475***	1.142***
	-12.61	-7.7	-12.46	-7.76
Board	0.194	-0.0682	0.200*	-0.0808
	-1.64	-0.49	-1.69	-0.58)
Lev	-0.246*	-0.307*	-0.247*	-0.309*
	-1.68	-1.70	-1.69	-1.74
Employee	0.0232	0.0221	0.023	0.0207
	-0.74	-0.48	-0.74	-0.44
Oversea	0.0305	-0.0353	0.0298	-0.0323
	-0.87	-0.78	-0.85	-0.71
_cons	-10.91***	-7.778***	-10.63***	-7.621***
	-14.29	-7.49	-13.94	-7.33
R2	0.335	0.322	0.337	0.321
N	16556	4212	16556	4212

T Statistics in Parentheses
* p<0.1, ** p<0.05, *** p<0.01

In the Chinese market, differences in policy resources and management incentives between state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) can impact strategic decision-making. To examine this, we analysed the effects of geographical and product diversification on digital transformation separately within SOEs and non-SOEs, with results presented in Table 9. Findings indicate that geographical diversification promotes digital transformation in both SOEs and non-SOEs by enhancing access to external resources, knowledge, and technology. However, while product diversification significantly benefits digital transformation in non-SOEs, this effect is not observed in SOEs.

Overseas Executives Vs. Non-Overseas Executives

The influence of diversification on digital transformation as strategic decisions is partially shaped by the foresight and cognitive abilities of senior management. To examine this, we split the sample into two groups: companies with executives who have overseas experience and those without. Regression analyses on each group, reported in Table 10, reveal that for companies with executives with overseas experience, geographical diversification positively impacts digital transformation. In contrast, this effect is not significant for companies without such executive experience. However, product diversification shows a positive impact on digital transformation across both groups.

Table 10: Results of Heterogeneity of Overseas Executives.

	(1)	(2)	(3)	(4)
	oversea_0_EDT	oversea_1_EDT	oversea_0_EDT	oversea_1_EDT
GD	0.00331	0.00397*		
	-1.4	-1.78		
PD			0.124***	0.0896**
			-3.12	-2.24
Size	0.275***	0.380***	0.270***	0.375***
	-5.66	-6.88	-5.53	-6.74
Age	1.530***	1.400***	1.517***	1.386***
	-11.68	-9.98	-11.65	-9.87
Board	-0.098	0.228*	-0.107	0.230*
	-0.68	-1.72	-0.75	-1.73
Lev	-0.233	-0.159	-0.247	-0.166
	-1.43	-0.98	-1.53	-1.02
Employee	-0.0129	0.0183	-0.0153	0.0175
	-0.40	-0.46	-0.48	-0.44
Soe	-0.0907	-0.128	-0.0945	-0.133
	-0.76	-1.23	-0.80	-1.27
_cons	-0.6	-0.52	-0.84	-0.63
	-8.584***	-11.28***	-8.370***	-11.10***
	-9.80	-12.21	-9.51	-11.89
R2	0.28	0.332	0.282	0.332
N	8961	11807	8961	11807

T Statistics in Parentheses
* p<0.1, ** p<0.05, *** p<0.01

East Regions Vs. Non-East Regions

Table 11: Results of Regional Heterogeneity of Enterprises.

	(1)	(2)	(3)	(4)
	east_0_EDT	east_1_EDT	east_0_EDT	east_1_EDT
DG	0.00255	0.00524***		
	-0.78	-2.7		
PD			0.0955	0.119***
			-1.39	-3.54
Size	0.272***	0.366***	0.267***	0.360***
	-4.62	-7.96	-4.52	-7.77
Age	1.230***	1.516***	1.229***	1.497***
	-9.03	-13	-9.04	-12.82
Board	0.169	0.0832	0.16	0.086
	-1.34	-0.67	-1.28	-0.7
Lev	-0.168	-0.262*	-0.179	-0.267*
	-0.96	-1.85	-1.02	-1.89
Employee	0.0357	0.00954	0.0339	0.00778
	-0.67	-0.34	-0.63	-0.27
Soe	-0.226**	-0.00226	-0.228**	-0.0074
	-1.99	-0.02	-1.99	-0.07
Oversea	-0.0682	0.0443	-0.0675	0.0443
	-1.40	-1.28	-1.38	-1.29
_cons	-8.776***	-10.92***	-8.628***	-10.68***
	-9.22	-13.43	-8.98	-13.04
R2	0.317	0.345	0.318	0.346
N	4946	15822	4946	15822

T Statistics in Parentheses
* p<0.1, ** p<0.05, *** p<0.01

Regional differences can influence the impact of diversification on digital transformation due to factors such as transportation and economic environment. To explore this, we divided the sample into two groups based on location: the eastern and non-eastern regions. Regression analysis on each subset, as shown in Table 11, reveals that both geographical and product diversification significantly enhance digital transformation only for enterprises in the

eastern region. For enterprises outside this region, neither form of diversification shows a significant effect on digital transformation.

Conclusion

This study analyses data from Chinese listed companies (2009–2021) to examine the impact of geographical and product diversification on digital transformation. Findings indicate that both diversification strategies significantly enhance digital transformation, supported by robustness and endogeneity tests. Heterogeneity analysis shows that while geographical diversification impacts both state-owned and non-state-owned enterprises similarly, product diversification significantly affects only non-state-owned enterprises. Firms with executives with overseas experience gain more from geographical diversification, and companies in eastern China show stronger digital transformation effects from both diversification types. Theoretically, these results expand the understanding of digital transformation by highlighting diversification as a strategic driver beyond traditional performance and innovation metrics, offering new insights into how diversification supports the knowledge, technology, and resources essential for digital transformation. Practically, enterprises should leverage geographical and product diversification to drive digital transformation, aligning strategies with regional resources and market diversity. State-owned enterprises could further explore product diversification, while overseas-experienced managers may better navigate geographical diversification. Regional economic factors also play a role in location-based strategic choices, enabling firms to optimize digital transformation through effective diversification.

Data Availability

Data will be made available on request.

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Appendix Table A1

Artificial Intelligence	Artificial Intelligence, Business Intelligence, Image Understanding, Investment Decision aid Systems, Intelligent Data Analysis, Intelligent Robotics, Machine Learning, Deep Learning, Semantic Search, Biometrics, Face Recognition, Voice Recognition, Identity Verification, Autonomous Driving, Natural Language Processing
Big Data	Big Data, Data Mining, Text Mining, Data Visualization, Heterogeneous Data, Credit, Augmented Reality, Mixed Reality, Virtual Reality
Cloud Computing	Cloud Computing, Streaming Computing, Graph Computing, In-Memory Computing, Multi-Party Secure Computing, Neuromorphic Computing, Green Computing, Cognitive Computing, Converged Architecture, Billion-Level Concurrency, EB-Level Storage, Internet of Things, Information Physical Systems
Blockchain	Blockchain, Digital currency, Distributed Computing, Differential Privacy Technology, Smart Financial Contracts
Applications of Digital Technology	Mobile Internet, Industrial Internet, Mobile Internet, Internet Healthcare, E-commerce, Mobile Payment, Third-party Payment, NFC Payment, Smart Energy, B2B, B2C, C2B, C2C, O2O, Smart Wear, Smart Agriculture, Smart Transportation, Smart Healthcare, Intelligent Customer Service, Smart Home, Smart Investment, Smart cultural Tourism, Smart Environmental Protection, Smart Grid, Smart Marketing, Digital Marketing, Unmanned Retail, Internet Finance, Digital Finance, Fintech, Financial Technology, Quantitative Finance, Open Banking

Appendix Table A2

Variables	**Variable Definition**	**Source**
	Dependent Variables	
EDT	The logarithm of 1 plus the frequency of occurrence of all digitalization-related keywords in the annual reports.	CSMAR
	Independent Variables	
GD	calculated based on the logarithm of the enterprise's exports	CHINA CUSTOMS DATABASE
PD	Measured by entropy index with the calculation as refers to the proportion of sales in the business segment	WIND
	Control Variables	
Size	Ln (Total Assets)	CSMAR
Age	Ln (year of establishment +1)	CSMAR
Board	Ln (1+ Number of Board Members)	CSMAR
Lev	Total liabilities/total assets	CSMAR
Employees	Ln (the number of employees)	CSMAR
Soe	1 for State-owned enterprises, 0 for others	CSMAR
Oversea	1 for the current supervisory board with an overseas background, 0 for others	CSMAR