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Article

Research on the Economic Effects of Enterprise Digital Transformation Driven by Intelligent Upgrade of Value Chain under the Enabling Role of Artificial Intelligence

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Abstract: With the rapid development of the digital economy, scholars have increasingly emphasized the role of digitalization in enhancing the value chain of enterprises. This paper takes manufacturing enterprises listed on the Shanghai and Shenzhen stock markets from 2014 to 2024 as the research sample to explore the impact of digital transformation enabled by artificial intelligence on the upgrading of the value chain of manufacturing enterprises, as well as the mechanism of the adjustment of human capital. The research finds that the effect of enterprise digital transformation on the intelligent upgrade of the enterprise value chain is significantly positive, with a stable coefficient, and has passed the robustness test. The mechanism test shows that enterprise digital transformation can promote the degree of intelligent upgrade of the value chain by optimizing human capital. Further heterogeneity analysis indicates that non-high-tech enterprises, large enterprises, industries with more intense competition, non-manufacturing industries, and enterprises in inland western regions and regions with higher development levels, have a greater and more significant effect on the value chain improvement through digital transformation. The promoting effect of digital transformation on the value chain upgrade of enterprises can effectively improve the business performance of enterprises. This research provides micro evidence from the perspective of the value chain for the integration effect of the digital economy and the real economy. The research conclusion has important policy implications for the formulation of digital policies and the breakthrough of China's manufacturing industry from the low-end lock of the global value chain.

Keywords: Enterprise digital transformation; Intelligent upgrade of value chain; Human capital; Mediating effect; Heterogeneity analysis

1. Introduction

In the current digital era, enterprises are confronted with increasingly fierce competition and rapidly changing market conditions. Digital transformation has become a crucial factor for the survival and development of enterprises [1]. And artificial intelligence (AI), as a transformative technology, is providing strong support for the digital transformation of enterprises [2-3]. One important aspect that AI can help enterprises achieve in digital transformation is to enhance data processing and analysis capabilities. In the digital business world, data is like the blood of an enterprise, continuously generating and flowing. However, if these massive amounts of data cannot be effectively processed and analyzed, they cannot provide valuable insights for the enterprise. The emergence of AI technology has changed this situation. Through machine learning and deep learning algorithms, AI can quickly and

accurately process and analyze large amounts of structured and unstructured data, helping enterprises discover patterns, trends, and relationships hidden in the data [4-6].

Regarding AI-driven enterprise digital transformation, literature [7] emphasizes that AI-driven enterprise digital transformation has become a key driving force for promoting enterprise innovation and efficiency improvement, and based on semi-structured interview methods and literature reviews, it indicates that the application of AI has many practical significances, but also faces risks in data security. Literature [8] examines the application of AI in the digital transformation of enterprise business strategies, believing that AI technology has great potential in solving various problems, but still faces many challenges, especially in how to strategically apply AI to create business value. Literature [9] analyzes the relationship between digital transformation and enterprise innovation performance, and research shows that digital transformation plays a key role in enhancing enterprise innovation performance, and AI is an important mediating factor in this process.

Furthermore, reference [10] elaborates that AI has significantly enhanced economic efficiency. To promote the development and application of AI technology, various governments have implemented a number of industrial policies. Therefore, this study examines the impact of these industrial policies on the digital transformation of enterprises. The results show that AI industrial policies accelerate the digital transformation of enterprises, especially having a significant effect on manufacturing enterprises and those with tight financial budgets. Reference [11] analyzes the impact of AI investment and data element accumulation on the performance of enterprise digital transformation. The research indicates that AI investment significantly improves the digital transformation performance of enterprises, providing important support for emerging research in the digital economy field. Reference [12] examines the development characteristics of modern digital technologies in optimizing enterprise management and proposes main measures for enterprise management optimization based on AI and big data applications. It emphasizes the urgency and necessity for enterprises to implement digital technologies to ensure their competitiveness and optimize production processes. Reference [13] investigates the application of AI technology in enterprise economic management, emphasizing that AI intelligent economic management is an important development direction for future digital transformation. The research results contribute to promoting the popularization of AI technology in enterprise economic management. Reference [14] analyzes the opportunities and risks brought by data-driven decision-making in the construction industry, using an integrated, interdisciplinary, and inclusive approach to provide guidance for AI application and assess its benefits and risks. Reference [15] examines the impact of digital transformation under the AI background on the economic resilience of the energy industry. Based on the analysis of the development difficulties of the energy industry and the integration of AI and digital transformation, a particle swarm optimization-based least squares support vector machine algorithm is proposed to verify the model's good predictive effect on the economic resilience index. Reference [16] analyzes whether and how AI applications can enhance the ESG performance of enterprises. The research shows that AI applications in enterprises have a positive impact on ESG performance, and the internal control system within the organization and the external information environment play a mediating role between AI and enterprise ESG performance. Reference [17] introduces the practical applications of logistics enterprises in applying cutting-edge digital technologies, aiming to help enterprises better understand how to achieve digital transformation through blockchain and AI, thereby enhancing their business competitiveness. Reference [18] emphasizes that leveraging advanced science and technology and digital technologies, digital transformation has become an important means to promote the sustainable development of enterprises, and by expanding the application of machine learning in economics, it provides a theoretical basis for enterprises to enhance digital transformation.

At the same time, the widespread application of AI is reshaping the traditional division of labor in the enterprise value chain [19]. On one hand, automation technologies represented by industrial robots, through enhancing labor productivity and product value-added, demonstrate significant potential for value creation; on the other hand, the continuous innovation, global diffusion, and deep application of AI technology are profoundly changing the production and organizational paradigms of enterprises, driving the value chain to ascend to higher value-added segments [20-22]. Existing studies have confirmed that AI can significantly enhance the GVC participation and division status of China's manufacturing industry through various channels such as reducing trade costs, improving total factor productivity, promoting technological innovation, and optimizing resource allocation [23-24]. In the future, the integration of AI with 5G, blockchain, and other digital technologies can not only improve the collaborative efficiency among value chain partners but also, to a certain extent, mitigate the negative impacts brought by population aging. Its application prospects are extensive, and its strategic value is increasingly prominent.

In view of this, this paper uses the text analysis method in machine learning to construct an

indicator of the digitalization degree of Chinese A-share manufacturing listed enterprises, empirically examines the impact of enterprise digital transformation on the upgrading of the enterprise value chain, and explores the intermediate influence mechanism of human capital. Based on this, further investigate the heterogeneity of the impact of enterprise digital transformation on the upgrading of the enterprise value chain, as well as the economic effect of enabling enterprise digital transformation with artificial intelligence to promote the intelligent upgrading of the value chain. This will provide theoretical guidance and empirical evidence for the formulation of China's digital economy policies and the upgrading of enterprise value chains.

2. Theoretical Analysis and Research Hypotheses

2.1. The Direct Impact of Enterprise Digital Transformation on the Upgrading of Value Chain

In the industrial value chain, the distribution of added value at different links often presents a "smile curve" shape. This theory is of great significance in analyzing the economic contributions of each link of the value chain. The impact of the digital economy on traditional enterprises can be summarized into two aspects. First, it optimizes resource allocation through technological innovation, improves production efficiency, and can significantly reduce costs. This transformation not only enhances the operational efficiency of enterprises but also brings higher-quality and lower-cost products and services to consumers. Second, the rise of enterprise digital transformation has given rise to new consumer demands and industrial models. These new demands and models, such as the sharing economy, e-commerce, and remote work, not only change people's lifestyles but also reshape market structure and competition patterns. During this process, the pull effect from the demand side is significant, prompting the supply side to constantly innovate to meet the constantly changing market demands. At the same time, this also promotes the integration of the value chain, optimizes the competitive relationship and industrial layout, and injects new vitality and development potential into traditional industries. The digital economy reshapes the industrial form, making the direction of enterprise digital transformation increasingly clear, and will trigger a new round of industrial transformation. The development of the digital economy has led to changes in the consumption concepts and demand preferences of social residents, as well as the investment concepts and industrial structure of producers, gradually transforming the market. This has a certain promoting effect on industrial upgrading. The digital economy provides efficient data processing capabilities, intelligent technologies, and new business models, which can significantly improve the efficiency, quality, and innovation capabilities of manufacturing industries, thereby promoting the upgrading of their value chains. The following hypothesis is proposed:

H1: Enterprise digital transformation has a positive effect on the intelligent upgrade of the value chain.

2.2. The Indirect Impact of Enterprise Digital Transformation on the Upgrading of Value Chain

The integration of the digital economy and the real economy is a dynamic process that progresses gradually. This dynamic process is influenced by various factors. This study mainly focuses on the general process of enterprise digital transformation and the upgrading path of enterprise value chains. From the perspective of the system structure of production factors, the process of digital technology penetrating enterprises is mainly achieved through the aggregation of human capital in manufacturing enterprises. The development of the digital economy and others has broken the time and space limitations for consumers and enterprises to acquire advanced knowledge, concepts, and technologies. Employees of enterprises can acquire the climb of the learning curve through network videos and online training, and their professional knowledge and professional skills are also continuously improving. Employees with advanced professional knowledge and skills can transform their work concepts through network knowledge, and enterprise employees, as the most important production factor, gradually flow to high-end industries with better working conditions, greater development space, and better welfare benefits, that is, enterprises with higher production efficiency. Human capital and other related factors will also flow from low-end manufacturing to high-end manufacturing, thereby promoting the transformation of low-end manufacturing to high-end enterprises. Enterprise digital transformation helps improve the professional knowledge and skills of enterprise employees, and also enables enterprise employees to obtain higher wages and salaries, further increasing the consumption level of enterprise employees. With the overall improvement of income levels, consumers will pursue higher quality of life after meeting basic needs, shift to more personalized and diverse consumption

preferences, and in this process, will also put forward higher requirements for product quality. During this process, the demand structure and commodity supply structure of the entire society will also move towards high-end, and the enterprise value chain will undergo intelligent upgrading. H2: Enterprise digital transformation under the empowerment of artificial intelligence promotes the intelligent upgrading of value chains by adjusting human capital.

3. Research Design

3.1. Sample Selection and Data Sources

This paper selects manufacturing enterprises listed on the Shanghai and Shenzhen stock markets from 2014 to 2024 as the sample. Firstly, it eliminates the ST and *ST samples as well as those with missing important variables. Secondly, it eliminates the samples with severe missing of core variables. Then, it uses interpolation methods to fill in the small amount of missing data. Finally, it truncates the tails of all continuous variables at the 1% and 99% quantiles. There are a total of 3221 listed enterprises with 18,505 enterprise-year observations. The specific data comes from the Guotaiyuan database, which provides basic information about the enterprise's operating conditions and financial indicators.

3.2. Definition of Key Variables

(1) Upgrading of the enterprise value chain

There is no unified and widely accepted method for measuring the upgrading of the enterprise value chain in the academic community. Although there are some indicator systems based on industry-level analysis, they are difficult to meet the needs of this paper's analysis based on micro-enterprise research. The upgrading of enterprises essentially requires increasing the added value of products, that is, enterprises move from low-end production to high-added-value products, accompanied by continuous upward movement of enterprises throughout the industrial chain or product value chain. Some studies take the degree of value increment of products as the most basic foothold of industrial upgrading, believing that the higher the added value rate of an industry (enterprise), the higher the value chain position it occupies. In fact, this is consistent with the "smile curve" theory, which holds that there are two forms of enterprise value chain upgrading: one is to climb towards the two ends of the smile curve, that is, value chain heightening; the other is that the middle part of the smile curve rises upwards, that is, processing degree upgrading. However, regardless of which form of upgrading, the final result is a transformation process of value added from low to high. Therefore, this paper adopts the approach of Yin Y et al. [25] and uses the added value rate, that is, the ratio of enterprise industrial added value to total output, as the measurement indicator for the upgrading of the enterprise value chain. The current industrial added value of the enterprise is equal to the sum of the following four items: (a) total salary (the amount paid to employees and the cash paid for employees plus the year-end number minus the beginning number); (b) enterprise profit (net profit minus non-operating income, investment income, fair value change gains and losses, exchange gains, plus non-operating expenses and asset impairment losses); (c) enterprise tax (business tax and surcharges, income tax minus subsidy income); (d) enterprise interest (interest payable).

The final calculation formula is: Current industrial added value = (payment to employees and the cash paid for employees + the year-end number of payable employee compensation) + (net profit - non-operating income - investment income - fair value change gains and losses - exchange gains + non-operating expenses + asset impairment losses) + (business tax and surcharges + income tax expenses - refund taxes) + interest payable. Added value rate = Added value / (Added value + cash paid for purchasing goods and accepting services).

(2) Enterprise digitalization level

This paper adopts the text analysis method in machine learning to analyze the "management discussion and analysis" section of listed enterprises and extract keywords related to digitalization to measure the digitalization level of listed enterprises. Keywords related to digitalization include keywords composed of basic vocabulary such as digital, data, intelligence, cloud, robot, electronic, 3D, AI, etc. This paper measures the digitalization level of enterprises using the natural logarithm of the frequency of digitalization words and takes the proportion of digital assets as a robust test for measuring the digitalization level of listed enterprises.

(3) Control variables

Control variables include: enterprise size (SIZE), debt-to-asset ratio (LEV), growth ability (GROWTH), fixed asset ratio (FIX), measured by the sum of the holdings of the top ten shareholders (TOP10); return on equity (ROA), measured by the ratio of after-tax profit to equity.

(4) Mediating variables

Human capital: The human capital in this paper is measured by the average years of education.

3.3. Measurement Model

This paper constructs a multi-dimensional fixed-effects econometric model to study the impact of enterprise digital transformation on the upgrading of the enterprise value chain:

$$VC_{ijkt} = \alpha_0 + \beta_1 Digital_{ijkt} + \sum Control + Firm_i + Industry_j + City_k + Year_t + \varepsilon_{ijkt} \quad (1)$$

Among them, i、j、k、t respectively represent enterprise, industry, province and year, VC_{ijkt} is an indicator depicting the upgrading of the enterprise value chain, $Digital_{ijkt}$ represents the enterprise's digitalization level, and $Control$ is the set of control variables at the enterprise level. The selection of control variables mainly follows the following principles: Firstly, variables that simultaneously affect both the enterprise's value-added rate and digitalization level should be controlled to eliminate confounding biases caused by confounding variables; Secondly, variables that are affected by digitalization level and will also affect the enterprise's value-added rate should be avoided from being controlled to avoid excessive control biases. $Firm_i$, $Industry_j$, $City_k$, $Year$ respectively represent fixed effects of enterprise, industry, province and year. According to theoretical analysis, we expect that the coefficient β_1 of $Digital$ is significantly positive, indicating that in the case where other variables remain constant, enterprise digital transformation can promote the economic effect of value chain upgrading.

4. Empirical Results and Analysis

4.1. Descriptive Statistics and Correlation Tests

(1) Descriptive Statistics

Table 1 presents the descriptive statistics of the variables, integrating all the variables and indicators used in this study. It describes the average value, standard deviation, minimum value, and maximum value of all the data. These include: the explained variable, Value Chain Intelligent Upgrade (VC); the explanatory variable, Digital Transformation; the mediating variable, Human Capital (Talent); and the control variables (SIZE, LEV, GROW, TOP10, ROE, FIX).

By conducting the descriptive statistics of the variables, a general understanding of the basic characteristics of the data was achieved. From the descriptive statistics test results in Table 1, it can be seen that the average value of enterprise value chain upgrade is 1.968, with a minimum value of 0.864 and a maximum value of 8.161, indicating a certain gap between the minimum and maximum values. This suggests a relatively large degree of data separation and an overall low level. There is still considerable room for development in the enterprise value chain. According to the results, the maximum value of the digital transformation degree of enterprises is 4.672, the minimum value is 0, and the average value is 1.257. This indicates that there are significant differences in the transformation degree of enterprises among different listed companies in China. There are also significant differences in the number of keywords related to digital transformation mentioned in the annual reports of different enterprises. Some enterprises still hold a conservative attitude towards digital transformation. Moreover, according to the research based on the innovation diffusion theory, the trend of digital transformation in China has not achieved the rapid expansion degree. The statistical characteristics of the control variables indicate that there are significant differences in company size, shareholding ratio, and fixed asset ratio among different listed companies.

Table 1. Descriptive statistics

Variable	N	Mean	SD	Minimum	Maximum
VC	18505	1.968	1.234	0.864	8.161
Digital	18505	1.257	1.277	0.000	4.672
Talent	18505	0.098	0.018	0.073	0.128
SIZE	18505	3.805	1.311	1.541	7.816
LEV	18505	0.43	0.215	0.061	0.908
GROWTH	18505	0.137	0.318	-0.575	1.577
TOP10	18505	0.558	0.22	0.000	0.914
ROA	18505	0.067	0.074	-0.215	0.265
FIX	18505	0.075	0.136	-0.641	0.379

(2) Correlation Test

The correlation coefficients among the main research variables in this paper are shown in Table 2. Note: *, **, and *** indicate significant correlations at the 10%, 5%, and 1% levels, respectively. The same applies below. By analyzing the correlation coefficients of each variable, it can be found that the upgrading of the company's value chain and digital transformation have a very obvious relationship at the 1% level. The higher the degree of digital transformation, the higher the degree of value chain upgrading of the enterprise. This preliminarily verifies the establishment of Hypothesis 1 in this paper, but the specific relationship needs further empirical verification; at the same time, by looking at the correlation coefficients among the variables in this paper, it can be known that the variables selected in this paper are relatively appropriate, and there is no obvious multicollinearity problem in this model.

Table 2. Correlation coefficient matrix

Variable	VC	Digital	Talent	SIZE	LEV	GROWTH	TOP10	ROA	FIX
VC	1								
Digital	0.031***	1							
Talent	0.134***	0.026***	1						
SIZE	0.199***	0.205***	0.025***	1					
LEV	0.069***	0.002***	0.561***	-0.042***	1				
GROWTH	-0.389***	0.109***	-0.015*	-0.275***	0.077***	1			
TOP10	-0.269***	0.005***	-0.325***	-0.331***	-0.203***	0.541***	1		
ROA	0.045***	0.045***	0.302***	0.001	0.287***	0.009	-0.005	1	
FIX	-0.119***	-0.067***	0.135***	-0.119***	0.128***	0.153***	-0.011	0.061***	1

4.2. Baseline Regression

Table 3 presents the fixed effect model estimation results of the impact of enterprise digital transformation on the intelligent upgrading of the value chain. The industry, region, and year fixed effects have also been controlled. In model (1), no control variables were set. Models (2) to (7) gradually added control variables. In the (1) column, the estimated coefficient of the impact of enterprise digital transformation (Digital) on the intelligent upgrading of the value chain (VC) is 0.0208, which passed the 1% statistical significance test. In the (2) to (7) columns, the estimated coefficients of the impact of enterprise digital transformation (Digital) on the intelligent upgrading of the value chain (VC) are all positive and passed the 1% statistical significance test. For example, in the (7) column, the estimated coefficient of the impact of enterprise digital transformation (Digital) on the intelligent upgrading of the value chain (VC) is 0.0168, which passed the 1% statistical significance test. By comparing the statistical results with and without control variables and by gradually adding control variables, it can be found that the effect of enterprise digital transformation on the intelligent upgrading of the enterprise value chain is significantly positive and the coefficient is stable, indicating that the estimation results have good reliability. This result shows that digital transformation is conducive to the intelligent upgrading of the value chain, and hypothesis H1 is established.

Table 3. Baseline Regression Results

Variable	VC						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Digital	0.0208***	0.0199***	0.0184***	0.0148***	0.0148***	0.0156***	0.0168***
	(0.0047)	(0.0047)	(0.0048)	(0.0048)	(0.0048)	(0.0049)	(0.0049)
ROA	——	0.0458***	0.0282***	0.0448***	0.0449***	0.0911***	0.0924***
		(0.0123)	(0.0129)	(0.0129)	(0.0131)	(0.0142)	(0.0142)
LEV	——	——	0.1992***	0.2364***	0.2296***	0.2537***	0.2441***
			(0.0377)	(0.0382)	(0.0385)	(0.0391)	(0.0394)
GROWTH	——	——	——	-0.5542***	-0.5859***	-0.6097***	-0.6038***
				(0.0389)	(0.0602)	(0.0607)	(0.0611)
TOP10	——	——	——	——	0.2077*	0.1127	0.1214
					(0.1135)	(0.1141)	(0.1145)
FIX	——	——	——	——	——	0.0058***	0.0059***
						(0.0009)	(0.0009)
SIZE	——	——	——	——	——	——	-0.0013
							(0.0045)
Constant	0.3321**	0.3011*	0.2314	0.4142**	0.4163**	0.0211	1.0151
	(0.1624)	(0.1629)	(0.1641)	(0.1635)	(0.1709)	(0.1781)	(10.922)
Year/Industry/Region Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Observed value	18505	18505	18505	18505	18505	18505	18505

R^2	0.0702	0.0724	0.0726	0.0821	0.0822	0.0908	0.0918

4.3. Robustness Test

(1) Instrumental Variable Method

Table 4 presents the results of the two-stage estimation. Columns (1) and (2) do not include control variables, while columns (3) and (4) do include control variables. The first column shows the estimation result of the first stage, that is, the result obtained by using the instrumental variable to estimate the endogenous explanatory variable. It shows that the estimated coefficient of the mean (mean_Digital) of the digital transformation of enterprises in the same city and the same industry is 0.8311, which passes the 1% statistical significance test, indicating that the correlation between the instrumental variable and the endogenous variable is significant. The second column shows the estimation result of the second stage. The coefficient of enterprise digital transformation (Digital) is estimated to be 0.0302, and it passes the 1% statistical significance test, indicating that the impact of enterprise digital transformation on the intelligent upgrade of the value chain is positive and significant. In columns (3) and (4), control variables are added, and the estimated coefficients and significance are not much different from those in columns (1) and (2). Thus, it can be known that the results obtained by estimating with the instrumental variable method and the results obtained by the benchmark regression maintain a good consistency.

Table 4. Robustness Test 1

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	stage I	**stage II**	**stage I**	**stage II**
	Digital	VC	Digital	VC
Mean_Digital	0.8311***	———	0.8264***	———
	(0.0091)		(0.0093)	
Digital	———	0.0302***	———	0.0274***
		(0.0066)		(0.0073)
Constant	0.8504	0.0577	0.0468	-0.7321
	(0.5353)	(0.3362)	(03709)	(0.4641)
Controlled variable	NO	NO	YES	YES
Year/Industry/Region Fixed Effect	YES	YES	YES	YES

(2) Shortening the sample time interval and excluding enterprises from municipalities

Table 5 presents the robustness test for shortening the sample time interval and excluding enterprises from municipalities.

This paper narrows the sample range to examine the impact of enterprise digital transformation on the intelligent upgrading of the value chain after 2015; firstly, considering that the pace of enterprise digitalization will accelerate under the national strategic background, which will change the effect on enterprise growth; secondly, the sample data closer to the present can better reflect the current situation. According to the estimation results in columns (1) and (2) of Table 5, without control variables and with control variables included, the estimated coefficients of enterprise digital transformation are 0.0291 and 0.0203, respectively, and pass the 1% statistical significance test; indicating that after shortening the sample interval, enterprise digital transformation still has a significant positive impact on the intelligent upgrading of the value chain, which is consistent with the baseline regression estimation results.

Municipalities in China have special characteristics. The conditions for enterprises within municipalities in terms of tax payment, obtaining incentive policies and financial support are different from those of enterprises in other regions. If these are taken into consideration, it may affect the estimation results. Therefore, the sample data of each municipality was excluded, and the test was re-conducted. According to the estimation results in columns (3) and (4) of Table 5, without control variables and with control variables included, the coefficients of enterprise digital transformation are estimated to be 0.0221 and 0.0169, respectively, and pass the 1% statistical significance test. The impact of enterprise digital transformation on the intelligent upgrading of the value chain is still significantly positive, and the conclusion has not changed. The above robustness tests indicate that the conclusion of enterprise digital transformation on the intelligent upgrading of the value chain is robust.

Table 5. Reduce the sample time and the robustness of the central government

Variable	VC			
	Short sample time interval		Excluding enterprises located in municipalities directly under the central government	
	(1)	(2)	(3)	(4)
Digital	0.0291***	0.0203***	0.0221***	0.0169***
	(0.0074)	(0.0076)	(0.0056)	(0.0055)
Constant term	0.0834	-0.2714	0.0812	-0.1632
	(0.1608)	(0.2215)	(0.3106)	(0.3943)
Controlled variable	NO	YES	NO	YES
Year/Industry/Region Fixed Effect	YES	YES	YES	YES
R^2	0.0892	0.1143	0.0785	0.1109

4.4. Mechanism Verification

To further test the research hypothesis 2 of this paper, the mediating effect of human capital was examined. The regression results are shown in Table 6. The detailed analysis is as follows:

(1) The column represents the test results of the degree of digital transformation on enterprise value. According to Table 6, the coefficient of the degree of digital transformation is 0.0168, and it is significantly positively correlated with the intelligent upgrading of the value chain at the 1% significance level. This indicates that the degree of digital transformation can significantly improve the degree of intelligent upgrading of the value chain, and hypothesis H1 has been verified. Moreover, this also conforms to the first step of the mediating effect test.

(2) The column represents the test results of the degree of digital transformation on human capital. The regression coefficient of the degree of digital transformation is 0.0122, and it has a positive impact on human capital at the 1% significance level. This shows that the degree of digital transformation can effectively promote the optimization of enterprise human capital. Moreover, this also conforms to the second step of the mediating effect test.

(3) This column is used to test whether human capital plays a mediating role. The regression results show that the coefficient of digital transformation is significantly positive, and the coefficient of the mediating variable is also significantly positive. That is, the coefficients d and b in step 3 are both significant, indicating an incomplete mediating effect. This means that the degree of digital transformation can promote the degree of intelligent upgrading of the value chain through the optimization of human capital, that is, the research hypothesis 2 of this paper is established. The above analysis indicates that the degree of digital transformation can promote the degree of intelligent upgrading of the value chain through the optimization of human capital.

Table 6. Inspection of the intermediary mechanism of human capital

Variable	(1)	(2)	(3)
	VC	Talent	VC
Digital	0.0168***	0.0122***	0.0351***
	(0.0049)	(5.622)	(2.621)
			14.4423***
			(4.722)
ROA	0.0924***	0.0151***	2.4222***
	(0.0142)	(9.981)	(6.222)
LEV	0.2441***	0.0051***	0.4881***
	(0.0394)	(5.221)	(4.288)
GROWTH	-0.6038***	0.0052***	-0.0153***
	(0.0611)	(22.225)	(-0.558)
TOP10	0.1214	-0.0454**	-0.6775**
	(0.1145)	(-0.592)	(-10.988)
FIX	0.0059***	-0.0012**	-0.0953**
	(0.0009)	(-1.213)	(-0.621)
SIZE	-0.0013	0.0083***	-0.6622***
	(0.0045)	(35.252)	(-18.122)
_cons	1.0151	0.0711***	2.2252***
	(10.922)	(20.225)	(9.52)
Year	Control	Control	Control
Industry	Control	Control	Control
Region	Control	Control	Control
F	232.225	433.114	176.798
N	18505	18505	18505
R-squared	0.322	0.622	0.298

5. Further discussion and analysis

5.1. Heterogeneity Analysis

(1) Analysis of Enterprise Heterogeneity

High-tech enterprises refer to those enterprises that possess independent intellectual property rights and core technologies in aspects such as technology development, transformation, and application. Enterprises recognized as high-tech enterprises exhibit differences in areas such as R&D investment, technological innovation capabilities, talent structure, market expansion, and government support. Additionally, high-tech enterprises generally demonstrate greater advancement and pioneering nature in digital transformation, and are more likely to achieve better results in this regard. Furthermore, the influence of enterprise asset size was also considered. The sample was divided based on whether the enterprise was recognized as a high-tech enterprise or a national key leading enterprise in agricultural industrialization, and whether the enterprise's asset size exceeded the median. This was done to further explore the heterogeneity effect of digital transformation on different types of agricultural enterprises in enhancing their enterprise value chains.

The regression results of the sample based on enterprise micro-characteristics are shown in Table 7. Compared with high-tech enterprises, non-high-tech enterprises have a greater effect of digital transformation on the enhancement of the value chain, and this effect is more statistically significant. This indicates that compared with traditional industries, these enterprises have a later-stage advantage in digital transformation, and non-high-tech enterprises have greater potential space in digital transformation. From the perspective of enterprise scale, compared with enterprises with smaller asset sizes, digital transformation has a more significant effect on enhancing the value chain level of large enterprises. Large enterprises usually have more core business processes and key resources, and the improvement effect of digital transformation on these processes is more important. In contrast, small enterprises often can only focus on a limited number of processes for digital transformation, so the effect of digital transformation that can be enhanced is relatively limited.

Table 7. The microscopic characteristics of the enterprise are returned to the results

Variable	(1) High-tech enterprise	(2) Nonhigh-tech enterprise	(3) Large scale	(4) Small size
Digital	0.323*(1.88)	0.399**(2.52)	0.221**(2.33)	0.345(1.41)
_cons	0.944**(2.12)	-0.192(-0.69)	-0.401*(-1.92)	-1.251(-1.65)
Control	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES
Year×Industry fixed effect	YES	YES	YES	YES

(2) Industry Heterogeneity Analysis

The characteristics of the same industry are also one of the important factors influencing the impact of digital transformation on the improvement of the enterprise value chain. The sample enterprises selected in this study cover agriculture, manufacturing, and services. Firstly, the level of industry competition will affect the impact of digital transformation on the improvement of the enterprise value chain. The sample regression results of industry characteristics are shown in Table 8.

The regression results are as shown in columns (1) and (2). For enterprises in industries with more intense competition, in order to continuously enhance their competitiveness and obtain more market share, the coefficient of digital transformation on the improvement of the value chain is larger and is more statistically significant. On the contrary, in industries with less intense competition, the impact of digital transformation on the improvement of the enterprise value chain is relatively small, because enterprises can rely on stable market demand and a certain profit level to survive. The impact of digital transformation on the improvement of enterprise competitiveness is limited. Secondly, there are differences in the impact of digital transformation on the improvement of the enterprise value chain between manufacturing and non-manufacturing industries. The regression results are shown in columns (3) and (4). Digital transformation has a significant positive impact on the improvement of the value chain for both types of enterprises, which is basically consistent with the baseline regression results. However, compared with manufacturing enterprises, the regression coefficient of digital transformation for non-manufacturing enterprises is larger. Due to the relatively mature production processes and higher production efficiency of manufacturing enterprises, the upstream and downstream supply chain

relationship has become the key to improving the value chain level. On the contrary, the production processes of non-manufacturing enterprises are relatively simple, and the upstream and downstream supply relationships are relatively single, so digital transformation mainly improves the value chain level through productivity improvement and cost savings, and the improvement effect is more prominent.

Table 8. The industry characteristics are returned to the sample

Variable	(1) Competitive high	(2) Competitive low	(3) Manufacturing	(4) Nonmanufacturing
Digital	0.301**(2.22)	0.465*(1.85)	0.252**(2.29)	1.075**(2.25)
_cons	0.194**(0.52)	-0.301(-0.82)	-0.097*(-0.45)	0.152(0.26)
Control	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES
Year×Industry fixed effect	YES	YES	YES	YES

(3) Regional Heterogeneity Analysis

Due to the uniqueness of the industry, its production efficiency and development level are often constrained by the regional endowment conditions. Moreover, the agricultural development level and industrial structure in different regions may also lead to the heterogeneity of the effect of digital transformation on the enhancement of the enterprise value chain. Therefore, this study examines the differences in the effect of digital transformation of enterprises in different regions on the value chain improvement from two dimensions: geographical location and development level. The regression results of the regional characteristic sample regression are shown in Table 9. Compared with the eastern coastal regions, the digital transformation in the western inland regions has a greater and more significant effect on the value chain improvement. Over the past few decades, the economic development mode in the western regions has been relatively extensive, with low resource utilization efficiency, and there is a large room for improvement. Therefore, in the production and manufacturing process, digital transformation has a more significant effect on improving production efficiency and resource utilization results. In contrast, compared with regions with a lower development level, regions with a higher development level have more mature and complete factor markets and product markets, so the effect of digital transformation on the enhancement of the enterprise value chain is also more significant.

Table 9. The region features a sample regression

Variable	(1) Eastern coast	(2) West	(3) High level	(4) Low level
Digital	0.263(1.55)	0.441***(2.66)	0.371***(3.38)	0.392*(1.75)
_cons	-0.009(-0.04)	-0.013(-0.05)	-0.877***(-3.45)	-0.202(0.26)
Control	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES
Year×Industry fixed effect	YES	YES	YES	YES

5.2. Analysis of Economic Consequences

Digital transformation is crucial for the growth of enterprises. The digital transformation of manufacturing enterprises optimizes the value creation methods in production, research and development, etc., which can enhance the sustained competitive advantages of enterprises and ultimately achieve the expansion of enterprise scale and benefits. Therefore, to test whether the promotion effect of digital transformation on the upgrading of the manufacturing enterprise's value chain can effectively improve the enterprise's operating performance, this paper uses the stepwise regression method to examine the economic effects brought by digital transformation to manufacturing enterprises. The Tobin's Q value, as an important market efficiency indicator, represents the efficiency and income ability of the comprehensive utilization of enterprise capital, and can show the enterprise's market operating performance from the aspects of profitability and market value. Therefore, this paper uses the Tobin's Q value as the proxy variable for enterprise operating performance. The economic consequences of digital transformation are tested as shown in Table 10. Firstly, by regressing Tobin's Q

as the dependent variable with the digital transformation variable, the results show that digital transformation has a significant positive promoting effect on the enterprise's operating performance. Secondly, in the above regression model, by successively adding the enterprise's research and development innovation (value_rd) and service operation (value_ser) variables, it can be seen from columns (2) and (3) that the regression coefficients of value_rd and value_ser remain significantly positive at the 1% or 5% level. This indicates that digital transformation prompts manufacturing enterprises to concentrate their advantageous resources on developing high value-added business such as upstream research and development innovation and downstream service operation, and under the joint effect of the "research and development innovation" and "service creation" effects, the enterprise's profitability and operating efficiency have been significantly improved, and ultimately the enterprise's operating performance has been enhanced.

Table 10. The economic consequences of the transformation of enterprise Numbers

Variable	(1)	(2)	(3)
Digital	0.6641***(3.912)	0.4711***(2.892)	0.6144***(3.333)
value_rd		0.0322***(2.641)	
value_ser			0.5025**(2.244)
_cons	15.7022***(12.551)	14.7852***(12.441)	14.7855***(12.605)
Control	YES	YES	YES
Year fixed effect	YES	YES	YES
Individual fixed effect	YES	YES	YES
R^2	0.2115	0.1414	0.2208
F	85.7251	59.2500	80.0500

6. Conclusion

Enterprise digital transformation is of vital importance in promoting the deep integration of China's digital economy and real economy, and achieving high-quality development of the manufacturing industry. This paper takes manufacturing listed companies from 2014 to 2024 as the research sample, and examines the impact of digital transformation and human capital structure adjustment on the upgrading of the manufacturing enterprise value chain. The research findings are as follows:

(1) The effect of enterprise digital transformation on the intelligent upgrading of the enterprise value chain is significantly positive and stable, which is conducive to the manufacturing enterprises climbing to the high value-added links at both ends of the "smile curve".

(2) Enterprise digital transformation can promote the degree of intelligent upgrading of the value chain by optimizing human capital.

(3) In terms of heterogeneity, from the perspective of enterprise micro-characteristics, in relatively traditional industries, non-high-tech enterprises have greater potential and space for digital transformation, and the digitalization degree has a greater effect on the improvement of the value chain, and is more statistically significant. The digital transformation of large enterprises has a more significant effect on improving the level of the enterprise value chain. From the perspective of industry characteristics, industries with more intense competition and non-manufacturing industries have more prominent improvement effects. From the perspective of regional characteristics, inland western regions and regions with higher development levels have greater and more significant improvement effects on the value chain through digital transformation. Therefore, corresponding digital transformation strategies need to be formulated based on different enterprise and regional characteristics to achieve the maximum value chain improvement effect.

(4) Economic consequence verification shows that the promotion effect of digital transformation on the value chain upgrading of manufacturing enterprises can effectively improve the enterprise's operating performance.

Based on this, the following policy suggestions are proposed:

First, at the government level. It is necessary to strengthen the construction of digital infrastructure, break through the infrastructure obstacles in digital transformation, provide complete software and hardware infrastructure key guarantees and element support for enterprise digital transformation, and promote the comprehensive upgrade of the connectivity among enterprises on the value chain.

Second, at the enterprise level. Firstly, it is necessary to realize that digitalization is the key engine for enterprise development, and must actively cultivate digital thinking, scientifically respond to the digital wave, accurately apply digital technology, and achieve the effect of enabling production and operation and ultimately upgrading the value chain. Secondly, strengthen the digital innovation attributes of enterprises, increase the introduction of high-tech talents, adopt on-the-job learning,

rotation training and other measures to improve the digital literacy of existing employees, and lay a more solid human capital foundation for further leveraging digitalization to promote the value chain climb of enterprises.

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