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The Impact of Digital Transformation on the Performance of Listed Automobile Manufacturing Enterprises in China

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Abstract

The paper investigates the impact of digital transformation on the performance of automobile manufacturing enterprises in China based on the sample data of 66 listed enterprises from 2012 to 2022, finding that digital transformation can improve the performance of automobile manufacturing enterprises and the improvement is long-term. Mechanism analysis shows that improving the human capital level of enterprises is an important path for digital transformation to promote enterprise performance. Moderating effect analysis shows that enterprise capacity has a significant moderating effect. Specifically, weaker business capacity undermines the positive effect of digital transformation on the performance of enterprises, and stronger development capacity plays a positive moderating role in the impact of digital transformation on the performance of enterprises. Heterogeneity analysis reveals that digital transformation has a more significant positive impact on the performance of non-state, small and medium-sized, and eastern automobile manufacturing enterprises. Based on the research conclusions, targeted policy recommendations are put forward to provide a reference for promoting digital transformation and the performance of automobile manufacturing enterprises.

JEL classification numbers: C12, M21.
Keywords: Digital Transformation, Automobile Manufacturing, Enterprise Performance.

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1. Introduction

As digital change is accelerating globally, the development of big data, cloud computing, artificial intelligence, blockchain, and other digital technologies has gained momentum. Currently, the digital economy is booming and has become a new economic form in China. In recent years, the scale of China's digital economy has maintained rapid growth. “The China Digital Economy Development Report” released by the China Academy of Information and Communication Technology in 2022 pointed out that the scale of China's digital economy reached 45.5 trillion yuan in 2021, accounting for 39.8% of GDP. It can be seen that the digital economy has become a key force driving China's economic development and an important growth pole for China's economy. However, the wave of digitalization is not only changing the market structure and consumption mode but also profoundly affecting the development of enterprises. The world has entered the VUCA era, with four distinctive features: Volatility, Uncertainty, Complexity, and Ambiguity. Meanwhile, the VUCA situation faced by enterprises has become more severe due to other factors such as geo-economics, awareness, and trade conflicts.

In this context, digital transformation has become the key to the survival of traditional manufacturing enterprises. Enterprises carrying out digital transformation can reduce costs, improve product quality, and ultimately achieve high-quality development. The automobile manufacturing industry has the characteristics of multi-level and wide field, and its development can not only affect the level of the national economy but also drive the development of many related industries. “China's Automobile Industry Development Report (2021)” pointed out that the automobile manufacturing industry is an important benchmark in the manufacturing industry, which will lead China from a large manufacturing country to a strong manufacturing country. Therefore, promoting the high-quality development of the automobile manufacturing industry is an important task at present.

The digital transformation of automobile manufacturing enterprises is a general trend with the consideration of the requirements of the national development goals and the change of market competition environment and industrial competition pattern. At present, many Internet companies are entering the car-making industry with a strong competitive advantage, and traditional automobile manufacturers must accelerate the construction of digital capabilities. Accordingly, does digital transformation have an impact on the performance of automobile manufacturing enterprises in China, and is the impact long-term? Does the impact vary depending on the ownership, size, and region of enterprises? Through what mechanisms does digital transformation affect enterprise performance? Is the impact of digital transformation on the performance of automobile manufacturing enterprises moderated by other factors? These questions need to be further explored.

2. Literature review

Scholars have not reached a unified conclusion on the connotation of digital transformation. Since enterprises are the main body of digital transformation, some scholars focus on digital technologies based on the perspective of enterprise change, stressing that enterprise digital transformation is understanding digital technologies and making digital technologies work for me (Tang and Jiang, 2021). Alessia et al. (2023) pointed out that digital transformation at the micro level implied changes in organizational roles, personal skills, leadership styles, and management approaches. Additionally, Vial (2019) viewed digital transformation as a process in which the application of digital technologies such as information, computing and communication brought changes in the attributes of entities that improve business strategies and operating models.

Whether or not the performance of the enterprise is affected by digital transformation has become a topic of great interest today. Some scholars believe that digital transformation has a positive impact on enterprise performance. Eller et al. (2020) found that IT adoption, employee skills upgrading and digital strategy significantly drove enterprises' digitalization, which in turn drove SMEs' financial performance. Zhai et al. (2022) suggested that digital transforma9tion brought lower costs, higher operational efficiency and better innovation to enterprises, improving their performance. Bouwman et al. (2019), through an empirical study of 321 European SMEs that actively utilize social media and big data, found that digital transformation led to the allocation of more resources to business model management and greater involvement of enterprises in strategy execution practices, which had a positive impact on their performance. Conversely, some scholars point out that enterprise digital transformation does not have a significant or even negative impact on performance (Liang et al., 2022). Akter et al. (2016) stated that enterprises developed big data capabilities to improve their performance levels, but the fact was that there were very few enterprises that could achieve this goal.

Having sorted out the direct effects of digital transformation on the performance of enterprises, it is also necessary to focus on the mechanisms by which digital transformation affects the performance of enterprises. From the perspective of innovation, in general, digital transformation is a driving force for enterprise innovation (Xu, 2020). More and more enterprises are now creating new production methods and innovative business models through digital transformation to gain new momentum for development (He, 2021). Sedera et al. (2016) stated that the development of digital platforms stimulated enterprise innovation. Cyrielle et al. (2022), using a sample of small enterprises in a middle-income country in South Africa, found that the use of digital communication technologies had a positive impact on enterprise innovation. Further, enterprise innovation has a positive impact on its performance. Jia (2021) pointed out that technological innovation outputs enabled enterprises to achieve high profits over a long period. In addition, based on a cost-control perspective, digital transformation can reduce the production costs of enterprises. Shivajee et al. (2019) found that the digitization of real-time data could reduce the conversion cost. Liu et al. (2022) suggested that digital transformation was effective in improving management efficiency and reducing the production and transaction costs of enterprises, which in turn improved the level of business performance.

The impact of digital transformation on enterprise performance is often moderated by other factors. Most studies focus on the moderating role of external environmental factors. Bai et al. (2022) pointed out that the impact of digital transformation on the financial performance of enterprises was moderated by ownership, industry type and the degree of intellectual property protection. The effect of digital transformation on financial performance was more significant in the case of state-owned manufacturing enterprises with a higher degree of intellectual property protection. Based on the environmental perspective, Meng et al. (2023) found that when firms faced a high level of environmental uncertainty, they would improve their adaptive capacity by optimizing the allocation of resources, which in turn promoted the level of enterprise performance. Based on the cultural perspective, Wang et al. (2022) suggested that the impact of digital technologies on enterprise performance was stronger in the context of Western culture. In addition, as data security is gaining traction, its moderating effect on the relationship between digital transformation and enterprise performance cannot be underestimated. Chi et al. (2023) found that data security negatively moderated the impact of digital manufacturing capabilities on enterprise performance, but positively moderated the impact of digital service capabilities on enterprise performance. Moreover, some scholars focus on the moderating effect of internal factors of enterprises, mainly from the perspectives of social responsibility and entrepreneurship. Nie (2023) pointed out that corporate social responsibility moderated the impact of digital transformation on enterprise performance. This moderating effect was more pronounced in industries with high research and development (R&D) intensity. When entrepreneurship was used as a moderating variable, Yang et al. (2021) found that transformational leadership had a positive moderating effect on the impact of digital transformation on enterprise performance.

By summarising the research of scholars, this paper finds that there are still some issues to be further explored. Firstly, in the current research on the relationship between digital transformation and enterprise performance, most scholars focus on all the listed manufacturing enterprises as a whole, and few studies focus on enterprises of manufacturing subsectors, especially the enterprises of automobile manufacturing. Secondly, research findings on the impact of digital transformation on enterprise performance have not reached a unanimous conclusion, meaning the impact needs to be further explored. Thirdly, current research mainly explores the impact mechanism of digital transformation on enterprise performance from the dimensions of technological innovation, enterprise cost and operational efficiency, and pays insufficient attention to the dimension of human capital. The labor force, which is one of the basic factors of production, has a significant impact on productivity and output quality. The cultivation and development of human capital is the key to improving the quality of the labor force, which can bring higher output for the enterprise. Therefore, the mechanism of enterprise human capital needs to be further explored. Fourthly, in terms of the moderating effect, most of the studies focus on external environmental factors, resulting in a lack of researches that focus on the moderating role of the internal factors of enterprises.

In summary, the possible marginal contributions of this paper lie in the following four areas: Firstly, this paper focuses the research object on listed automobile manufacturing enterprises in China and reconstructs an enterprise digital transformation dictionary based on previous research to accurately measure the digital transformation index of enterprises. Secondly, after completing the exploration of the impact of digital transformation on enterprise performance based on all the samples, this paper further explores the characteristics of long-term of the impact, as well as the heterogeneity of the impact with the consideration of enterprise characteristics such as size, ownership and region. Thirdly, this paper explores the mechanism by which digital transformation affects enterprise performance from the perspective of human capital, to complement the results of existing studies. Fourthly, based on the internal perspective of enterprises, this paper explores the moderating role of the enterprise business capacity and development capacity separately to enrich the existing research. This paper can provide unique theoretical guidance for different kinds of automobile manufacturing enterprises to apply digital transformation strategies and provide a reference for the government to formulate targeted digital transformation policies.

3. Theoretical Analysis and Research Hypothesis

3.1 The impact of digital transformation on the performance of automobile manufacturing enterprise in China

Based on the perspectives of production, digital transformation can reduce production costs and improve the performance of automobile manufacturing enterprises. On the one hand, enterprises can upgrade their business processes with the help of digital technologies, thus directly reducing production costs (Gölzer and Fritzsche, 2017). On the other hand, the application of digital technology enables enterprises to form an automated and batch production mode, which in turn reduces the rate of defective products (Wang and Zhang, 2022). Secondly, digital transformation enhances the ability of enterprises to identify the needs of different groups and satisfy the different needs of consumers by providing differentiated products (Jiang et al, 2023), which in turn can bring profit growth to enterprises. Thirdly, digital transformation helps enterprises optimize the allocation and service efficiency of production resources.

Based on the perspective of sales, enterprise digital transformation helps to reduce the cost of sales, expand the scope of product sales, and increase revenue. For example, with the rise of e-commerce platforms and online shopping, products are put on the Internet. The new sales model helps enterprises eliminate offline marketing costs. Secondly, the digital transformation of enterprises accelerates innovation, which helps to improve the quality and value of products and services, and enhances the core competitiveness of enterprises (Li, 2020).

Based on the perspectives of management and organization, digital transformation helps to improve the management efficiency of automobile manufacturing enterprises firstly, which in turn improves enterprise performance. On the one hand, digital transformation makes enterprise management more agile due to the versatility and connectivity features of digital platforms, enabling enterprises to respond quickly in the face of emergencies (Zeng et al., 2021). On the other hand, the application of digital technology optimizes enterprise business processes, resulting in more coordinated cooperation between departments (Verhoef et al., 2021). Secondly, enterprises are able to efficiently carry out organizational construction, resource allocation and opportunity development through the implementation of a digital strategy, which helps to enhance organizational resilience and promote sustainable development of enterprises, thereby achieving long-term profit growth (Meng et al., 2023). In addition, digital transformation improves the ability of enterprises to identify and acquire external information. By absorbing new knowledge and ideas, enterprises become more innovative and flexible (Xiao et al., 2023).

Therefore, based on the above analyses, hypothesis 1 is proposed.

Hypothesis 1: *Digital transformation has a positive impact on the performance of automobile manufacturing enterprises in China.*

3.2 The mechanism of enterprise human capital

Digital transformation has a positive impact on human capital in automobile manufacturing enterprises. Firstly, digital transformation improves the level of human capital of automobile manufacturing enterprises through the effect of technological substitution. The application of digital technology and intelligent equipment led to the replacement of some simple and repetitive labor by machines, reducing the demand for low-skilled labor in enterprises (Yami et al., 2021). However, work that requires higher cognitive skills cannot be completely replaced by intelligent equipment. Secondly, enterprises need the support of more specialized talent to make digital transformation sustainable. On the one hand, the information overload generated by digital transformation led to an increase in the demand for highly skilled personnel in enterprises (Bresnahan et al., 2002). Specifically, the use of information technology produces a large amount of data, which can be useful only through further processing and analysis. If the level of enterprise human capital cannot adapt to the rapid growth of data, information overload will occur. On the other hand, with the deep integration of digital technology with the production and operation activities of enterprises, a series of highly skilled jobs will be created, which helps to optimize the structure of enterprises' human capital. (Wadley, 2021). An increase in the level of human capital contributes to the performance of enterprises (Hitt et al., 2001). As one of the important resources, human capital is the basis for automobile manufacturing enterprises to sustainably gain core competitive advantages.

Firstly, the resource-based view explains how human capital enables enterprises to achieve sustained competitive advantage. Human capital is characterized by scarcity, irreplaceability and inimitability, and when it is tied to an enterprise, it can lead to higher returns. Secondly, human capital, with its rich knowledge base and strong learning capacity, helps to improve the efficiency of enterprises' innovation investment and the quality of innovation output, which in turn promotes the growth of enterprise performance. (Zhu and Gao, 2021). On the one hand, human capital promotes enterprise exploratory innovation, enabling enterprises to form technological barriers and further develop emerging markets. On the other hand, excellent human capital can acquire, filter, refine, locate and understand external heterogeneous knowledge through inter-organizational learning activities and integrate the new knowledge with existing knowledge within the enterprise, which contributes to the enhancement of enterprise performance through knowledge innovation. Thirdly, in addition to R&D personnel, the executive team, as another important component of human capital, is responsible for the enterprise's overall strategic decisions (Liu and Xu, 2020), which has a direct impact on the level of enterprise performance. In general, both in terms of market share and profit, the level of education and educational programs of executive team members are significantly and positively related to enterprise performance (Hambrick et al., 1996). Finally, based on a better reputation and position in the social network of human capital, enterprises have more opportunities to cooperate with other advanced enterprises in R&D projects, which in turn improves enterprise performance. (Liu et al., 2017).

Therefore, based on the above analyses, hypothesis 2 is proposed.

Hypothesis 2: *Digital transformation can improve the performance of automobile manufacturing enterprises in China by way of enhancing human capital levels*.

3.3 Moderating effects of enterprise capacity

Based on the perspective of internal factors of enterprises, this paper explores the moderating effects of the business capacity and development capacity of enterprises respectively.

3.4 The moderating effect of enterprises' business capacity

There is a strong correlation between the profitability and the business capacity of an enterprise (Yuan, 2009). The moderating effect of enterprise business capacity is shown in the following three points.

Firstly, stronger business capacity is inextricably linked to competent managers. On the one hand, competent managers are usually more aware of digital transformation and invest more money in digital projects, which is conducive to the advancement of digital transformation. On the other hand, based on a high degree of cognitive flexibility, competent managers can actively deal with the difficulties encountered in digital transformation (Gao and Li, 2022), which creates more value for the

enterprise and strengthens the positive impact of digital transformation on enterprise performance. Secondly, greater business capacity also implies a stronger competitive advantage for the enterprise, which not only helps the enterprise gain access to digital resources but also attracts the inflow of external capital. As a result, financing constraints are eased, providing financial support for digital transformation. Thirdly, the business capacity of the enterprise reflects its advanced business philosophy, which is like an invisible hand that regulates the mindset of employees as well as the environmental atmosphere within the enterprise. Under the guidance of the business philosophy, employees change their thoughts and correct their behavior (Jin, 2011). As a result, employees consciously improve their digital awareness and learn knowledge of digital technology, which helps to improve the efficiency of digital transformation and enhances the positive impact of digital transformation on enterprise performance.
Therefore, based on the above analyses, hypothesis 3 is proposed.

Hypothesis 3: *The improvement of the business capacity of enterprises can enhance the positive impact of digital transformation on the performance of automobile manufacturing enterprises in China.*

3.4.1 The moderating effect of enterprises' development capacity

Usually, development capacity refers to the future development trend of the enterprise's operation activities and the potential for enterprise development, which can also be called growth capacity. Enterprises that lack development capacity building may make poor business decisions that negatively affect their profitability. The moderating effect of the development capacity of enterprises is mainly reflected in the following three points.
Firstly, the enterprise with strong development capacity tends to expand the asset scale, which reflects its stage of development. At the early stage of development, enterprises are smaller and less risk-resistant. As the scale increases, the business activities of the enterprise become more stable, which is conducive to the digital transformation of the enterprise (Zhang et al., 2012). On the other hand, the expansion of scale also includes digital assets, which lay a solid foundation for enterprises to carry out digital transformation. Secondly, stronger development capacity usually implies a more rational capital structure, which helps to reduce the cost of financing and improve the ability to resist risks (Lin, 2023). Enterprises encounter a variety of risks and obstacles in the process of digital transformation, requiring them to have a sound capital structure. Thirdly, the intrinsic quality of development capacity is cultural competence, which is moreover the driving force for the sustainable development of enterprises. On the one hand, the enterprise culture is the starting point for the evaluation of enterprises by the public. An excellent enterprise culture can be recognized by the public and can attract more external funds for investment to support the digital transformation of enterprises. On the other hand, an excellent enterprise culture can enhance the sense of identity

of employees. As a result, employees will take a more positive attitude towards their work, learn and implement the enterprise's digital transformation strategy, and thus realize the common development of the individual and the enterprise, creating more value for the enterprise.
Therefore, based on the above analyses, hypothesis 4 is proposed.

Hypothesis 4: *The improvement of the development capacity of enterprises can enhance the positive impact of digital transformation on the performance of automobile manufacturing enterprises in China.*

4. Research Design

4.1 Sample selection and data sources

This paper selects automobile manufacturing enterprises listed in Shanghai and Shenzhen A-shares from 2012 to 2022 as the research object using the “Guidelines for Industry Classification of Listed Companies” issued by the China Securities Regulatory Commission as the standard. The principles of sample selection in this paper are as follows: (1) Listing dates before 2012 and enterprises still in existence in 2022 to ensure sample consistency; (2) ST and *ST listed enterprises are excluded; (3) Listed enterprises with serious missing data or obvious data anomalies are excluded. This paper finally determines the research sample as 66 listed automobile manufacturing enterprises in China from 2012 to 2022, with a total of 726 observations. The data of listed enterprises mainly come from the CSMAR and Wind database, and some missing data are manually calculated with the help of annual reports and social responsibility reports.

4.2 Variable design

4.2.1 Dependent variable

Enterprise performance can generally be divided into two categories: financial performance and non-financial performance. Financial performance can better reflect the operating conditions and profitability level of the enterprise over a period, which can be used as a signal of development potential. In addition, most scholars choose financial indicators to measure enterprise performance due to their accuracy, ease of access and high completeness. In summary, referring to the study of Yang et al. (2015), this paper selects the return on assets (ROA) as a proxy variable for enterprise performance. In general, the larger the value of ROA, the higher the level of enterprise performance. In addition, this paper uses return on equity (ROE) as a proxy variable for enterprise performance in the robustness test.

4.2.2 Independent variable

The steps to measure the digital transformation index of automobile manufacturing enterprises are as follows. Firstly, referring to the study of Zhao et al. (2021), this paper divides enterprise digital transformation into four dimensions: digital technology application, Internet business model, intelligent manufacturing and modern information system, and constructs the basic dictionary of digital transformation. Secondly, this paper expands the basic dictionary of digital transformation with reference to Wu et al. (2021), and the final dictionary is shown in Table 1. Thirdly, the digital transformation keywords appearing in the annual reports of enterprises are captured by text mining, and the word frequency counts of different dimensions are summed up. Fourthly, the entropy value method is used to determine the weights of each indicator to obtain the enterprise digital transformation index (DT).

Table 1: Dictionary of Enterprise Digital Transformation

Dimension	Participle dictionary
Digital technology applications	Data Management, Data Mining, Data Networking, Data Visualization, Data Platform, Data Center, Data Science, Digital Control, Digital Technology, Digital Communication, Digital Network, Digital Intelligence, Digital Terminal, Digital Marketing, Intelligent Environmental, Intelligent Customer Service, Intelligent Transportation, Digitization, Big Data, Cloud Computing, Streaming Computing, Cloud IT, Cloud Ecology, Cloud Services, Cloud Platform, Blockchain, Internet of Things, Machine Learning, Deep Learning, Natural Language Processing, Text Mining, Bioidentification Technology, Speech Recognition, Authentication.
Internet business models	Mobile Internet, Industrial Internet, Internet Solutions, Internet Technology, Internet Thinking, Internet Action, Internet Business, Internet Mobile, Internet Application, Internet Marketing, Internet Strategy, Internet Platform, Internet Model, Internet Business Model, Internet Ecology, Internet Finance, E-commerce, Digital Currency, Third Party Payment, NFC Payment, Unmanned Retailing, Internet, Internet Plus, Online to Offline, Online and Offline, O2O, B2B, C2C, B2C, C2B.
Intelligent manufacturing	Artificial Intelligence, High-end Intelligence, Industrial Intelligence, Mobile Intelligence, Business Intelligence, Intelligent Control, Intelligent Terminal, Intelligent Mobility, Intelligent Management, Intelligent Factory, Intelligent Logistics, Intelligent Manufacturing, Intelligent Warehousing, Intelligent Technology, Intelligent Equipment, Intelligent production, Intelligent Network, Intelligent Systems, Intelligent Energy, Intelligent, Automatic Control, Automatic Monitoring, Automatic Surveillance, Automatic Detection, Automatic Manufacturing, CNC, Integration, Integrated Solution, Integrated Control, Integrated System, Decision Support System, Intelligent Data Analysis, Industrial Cloud, Future Factory, Intelligent Troubleshooting, Life Cycle Management, Manufacturing Execution System, Virtualization, Virtual Manufacturing, Autonomous Driving.
Modern information systems	Information Sharing, Information Management, Information Integration, Information Software, Information Systems, Information Networks, Information Terminal, Information Center, Informatization, Cyber-Physical Systems, Internet Connection, Networking, Industrial Information, Industrial Communication.

4.2.3 Mechanism variable

Enterprise human capital (Hc). Referring to the study of Huang et al. (2015), the proportion of employees with bachelor's degrees and above to the total number of employees is chosen as a proxy variable for the human capital of an enterprise. The reason for choosing this indicator lies in the fact that with the improvement of China's education level, enterprises put forward higher requirements for employees' qualifications, and a college degree or below can no longer meet the production demands of enterprises.

4.2.4 Moderating variables

Based on the internal perspective of enterprises, this paper explores the moderating effect of enterprise capacity with two moderating variables, business capacity and development capacity. For the business capacity, the ratio of fixed assets to operating income is used to express it according to the study of Rong and Han (2018). The higher the ratio, the lower the utilization efficiency of the enterprise's assets, which further reflects the low level of the enterprise's operation and management. For enterprise development capacity, this paper selects the growth rate of total assets as a proxy variable, which is expressed as the ratio of total assets increment to the initial value of total assets. The higher the ratio, the stronger the enterprise development capacity.

4.2.5 Control variables

To avoid model bias caused by omitted variables, this paper refers to related studies (Wang et al., 2021; Li and Geng, 2021) and sets the following five control variables: (1) Enterprise age (Age). The difference between the current year and the enterprise's establishment date is used to measure the age of the enterprise and is taken as the logarithm. (2) Enterprise size (Size). It is expressed as the total assets of the enterprise and is treated logarithmically. (3) Asset-liability ratio (Lev). Expressed as the ratio of total liabilities to total assets, which directly reflects the capital structure of the enterprise. (4) Ownership concentration (Share). This paper uses the sum of the shareholding ratio of the top 5 shareholders of the enterprise as a proxy variable for ownership concentration. (5) Cash flow strength (Cash). The ratio of cash inflow from operating activities to total assets is used to measure cash flow strength.

To summarise, all the variables in this paper are shown in Table 2 below:

Table 2: Variable description

Classification	Name	Symbol	Definition
Dependent variable	Enterprise performance	ROA	Net Profit / Total Assets
Independent variable	Digital transformation	DT	Specific measurement
Mechanism variable	Enterprise human capital	Hc	Employees with Bachelor's Degree or Above / Total Employees
Moderating variables	Business capacity	Bc	Fixed Assets / Operating Revenue
	Development capacity	Dc	(Ending value of total assets for the period - beginning value of total assets for the period) / (Beginning value of total assets for the period)
Control variables	Enterprise age	Age	The difference between the current year and the enterprise's establishment date, with logarithmic treatment
	Enterprise size	Size	Total assets of the enterprise, with logarithmic treatment
	Asset-liability ratio	Lev	Total Liabilities / Total Assets
	Ownership concentration	Share	The sum of the top 5 shareholders' shareholding
	Cash flow strength	Cash	Cash Inflow from Operating Activities / Total Assets

4.3 Model design

4.3.1 Benchmark regression model

Considering that there may be differences in the development of each enterprise and that enterprise performance may be affected over time, it is more reasonable to construct a two-way fixed effects model for time and individuals. Based on hypothesis 1, the benchmark regression model (1) is constructed to explore the direct impact of digital transformation on the performance of automobile manufacturing enterprises in China.

$$ROA_{it} = \beta_0 + \beta_1 DT_{it} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where ROA_{it} represents the performance of enterprise i in year t. DT_{it} indicates the degree of digital transformation of enterprise i in year t. β_0 is the constant term, and β_1 is the regression coefficient of the core explanatory variable of digital transformation. $Control_{it}$ represents a set of control variables. μ_i and λ_t are individual fixed effects and time fixed effects respectively, and ε_{it} is the random error term.

4.3.2 Mechanism testing model

This paper proposes a mechanism research with reference to the method proposed by Jiang (2022). Firstly, this paper analyses the impact of human capital on the performance of automobile manufacturing enterprises based on literature and economic theory. Secondly, this paper focuses on the impact of digital transformation on the mechanism variable. Model (2) is constructed to explore the mechanism by which digital transformation affects the performance of automobile manufacturing enterprises in China from the perspective of enterprise human capital.

$$HC_{it} = \alpha_0 + \alpha_1 DT_{it} + +\gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Where HC_{it} represent the level of human capital of enterprise i in year t. Specifically, if the coefficient α_1 is significant, it indicates that digital transformation affects the level of human capital of the enterprise, while the impact of human capital on enterprise performance is obvious and well-founded. So it can be concluded that human capital is the mechanism by which digital transformation affects the performance of the enterprise.

4.3.3 Moderating effects model

In order to test the moderating effect of enterprise capacity, this paper constructs models (3) and (4) based on hypotheses 3 and 4. Specifically, based on the benchmark regression model, the interaction term between the moderating variables and digital transformation is introduced and decentred, while keeping the control variables constant.

$$ROA_{it} = \chi_0 + \chi_1 DT_{it} + \chi_2 Bc_{it} + \chi_3 Bc_{it} * DT_{it} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$ROA_{it} = \varphi_0 + \varphi_1 DT_{it} + \varphi_2 Dc_{it} + \varphi_3 Dc_{it} * DT_{it} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

Where $Bc_{it} * DT_{it}$ is the interaction term between business capacity and the digital transformation of automobile manufacturing enterprises. $Dc_{it} * DT_{it}$ is the interaction term between development capacity and digital transformation.

5. Empirical Results and Analysis

5.1 Descriptive statistics and multicollinearity test

The descriptive statistics of the variables are shown in Table 3 below. The maximum and minimum values of ROA are 0.221 and -1.13 respectively, indicating that there is a gap in the performance of automobile manufacturing enterprises in China, and also reflecting the strong representativeness of the sample selection in this paper. Large differences in enterprise performance may be related to enterprise characteristics such as size, number of years on the market, and equity concentration. From the perspective of the independent variable, the mean value of enterprise

digital transformation is 0.038, indicating that most automobile manufacturing enterprises in China already have the digital foundation to carry out transformation work and are in the early stage of transformation. Specifically, the maximum value of digital transformation is 0.465, indicating that there are enterprises with a high degree of digital transformation and are in a leading position. while the minimum value of 0 shows that there are still enterprises that lack awareness of digital transformation and have not yet implemented a digital transformation strategy.
Multicollinearity affects the results of the model regression, so this paper conducts the multicollinearity test for all the variables. The results are shown in Table 4 below. It can be seen that the variance inflation factor of all the variables is less than 5, indicating that there is no multicollinearity problem and the model regression results are reliable.

Table 3: Descriptive statistics

VarName	N	Mean	Min	Max	Median	SD
ROA	726	0.025	-1.127	0.221	0.031	0.072
DT	726	0.055	0	0.465	0.038	0.059
Hc	726	0.227	0.015	0.716	0.196	0.141
Inno	726	0.044	0	0.356	0.041	2.761
Dc	726	0.124	-0.642	8.337	0.077	0.456
Bc	726	0.385	0.015	2.852	0.299	0.294
Age	726	2.921	1.386	3.546	2.977	0.337
Size	726	22.82	17.02	27.62	22.64	1.416
Lev	726	0.427	0.066	1.413	0.416	0.169
Share	726	0.539	0.162	0.992	0.516	0.161
Cash	726	0.639	0.001	1.894	0.593	0.313

Table 4: Multicollinearity test

Variable	VIF	1/VIF
DT	1.340	0.745
Hc	1.190	0.839
Inno	1.390	0.717
Dc	1.090	0.915
Bc	1.990	0.504
Age	1.570	0.637
Size	1.550	0.644
Lev	1.370	0.731
Share	1.220	0.822
Cash	1.620	0.618
Mean	VIF	1.760

5.2 Benchmark regression analysis

5.2.1 Results analysis

First of all, this paper respectively conducts the F test and Hausman test. The P-value of the F test is 0, which rejects the original hypothesis that there are no fixed effects, suggesting that the choice of the fixed effects model is better than the mixed regression model. The P-value of the Hausman test is 0.0041, which is significant at the level of 1%, rejecting the original hypothesis that the random effect model is efficient. In summary, the fixed effect model is selected in this paper. Table 5 below reports the benchmark regression results. To ensure the robustness of the results, this paper uses stepwise regression with gradually increasing control variables for parameter estimation.

Regression (1) introduces digital transformation as an independent variable and controls for time and individual fixed effects, with no control variables included. The results show a positive correlation between digital transformation (DT) and enterprise performance (ROA) at the 1% significance level, suggesting that digital transformation enhances the performance of automobile manufacturing enterprises in China. Columns (2)-(4) show the results of the regression with control variables added stepwise to regression (1). Overall, the coefficients of digital transformation in all three models are significantly positive at the 1% level, indicating that the higher the degree of digital transformation, the higher the performance of the enterprise, which verifies the research hypothesis 1 proposed in this paper. Specifically, the coefficient of digital transformation in column (4) indicates that for every unit increase in the degree of digital transformation, enterprise performance improves by 0.1096 units. Comparing the results of regressions (1) and (4), it can be seen that the coefficient of digital transformation decreases from 0.1203 to 0.1096, with no change in significance, probably because some of the factors affecting the performance of the enterprise are absorbed when the model incorporates all the control variables.

Table 5: Results of the benchmark regression model

	(1)	(2)	(3)	(4)
	ROA	**ROA**	**ROA**	**ROA**
DT	0.1203***	0.1465***	0.1277***	0.1096***
	(3.23)	(3.69)	(3.62)	(3.72)
Lev		-0.3298**	-0.3353**	-0.3365**
		(-2.33)	(-2.36)	(-2.31)
Age		0.0829**	0.0852**	0.0633**
		(2.56)	(2.55)	(2.21)
Size			0.0145**	0.0153**
			(2.47)	(2.00)
Share				-0.0566
				(-0.55)
Cash				0.0466***
				(3.75)
Constant	0.0391***	-0.0441	-0.3687**	-0.3282**
	(6.65)	(-0.79)	(-2.59)	(-2.08)
Year	YES	YES	YES	YES
Individual	YES	YES	YES	YES
N	726	726	726	726
R^2	0.0945	0.3178	0.3283	0.3456
R^2_a	0.0806	0.3053	0.3151	0.3309
F	5.3039***	6.5012***	6.3239***	5.8265***

Note: (1) *, **, and *** represent the significance levels of 10%, 5%, and 1% respectively, and the same below; (2) Values in parentheses are t-values, and the same below.

Based on the perspective of control variables, the coefficient of the asset-liability ratio is significantly negative, indicating that the current level of assets and liabilities of most enterprises is in the unreasonable range, with higher financial risks and restricted business activities. Enterprise age is significantly and positively related to enterprise performance, probably because enterprises that have been on the market for a longer time have an advantage in terms of resource acquisition and strategy formulation, which is conducive to the enhancement of enterprises' profitability. The coefficient of size is significantly positive at the 5% level. The impact of ownership concentration on the performance of enterprises is negative but does not pass the significance test. The coefficient of cash flow strength is significantly positive at the 1% level. The higher the cash flow strength, the more stable financial support it can provide for the enterprise's R&D activities, which in turn improves the enterprise's performance.

5.2.2 Robustness tests and endogeneity test

To ensure the accuracy of the benchmark regression model, this paper conducts robustness tests by replacing the dependent variable and adjusting the sample intervals. Firstly, the return on assets (ROA) is replaced by the return on equity

(ROE) to represent the performance of automobile manufacturing enterprises. The new benchmark regression results are shown in columns (1) and (2) of Table 6 below. Secondly, the sample interval is adjusted to 2014-2022 in this paper due to the high level of uncertainty faced by newly listed enterprises, and columns (3) and (4) in Table 6 show the results of the new benchmark regression model.
The coefficients of digital transformation in Table 6 are all significantly positive at the 1% level, meaning that digital transformation promotes the performance of automobile manufacturing enterprises, which is consistent with the benchmark regression results above. In addition, the sign and significance of the control variables remain unchanged, also implying that the findings of this paper are robust.

Table 6: Robustness test results of the benchmark regression model

	(1)	**(2)**	**(3)**	**(4)**
	ROE	**ROE**	**ROA**	**ROA**
DT	0.2743***	0.2413***	0.1421***	0.1385***
	(3.18)	(3.55)	(3.51)	(3.78)
Constant	0.0773***	-0.8408	0.0398***	-0.7732***
	(6.78)	(-1.38)	(8.68)	(-3.17)
Control variables		YES		YES
Year	YES	YES	YES	YES
Individual	YES	YES	YES	YES
N	726	726	594	594
R^2	0.1004	0.1849	0.0843	0.3734
R^2_a	0.0866	0.1665	0.0702	0.3583
F	5.0336***	6.6847***	5.0968***	5.5255***

Furthermore, digital transformation can improve the performance of automobile manufacturing enterprises, but high-performing enterprises are more inclined to carry out digital transformation. Therefore, this paper uses the instrumental variable method and the Heckman two-step method to deal with possible endogeneity issues. Referring to the method proposed by Ni and Liu (2021), the average level of digital transformation of enterprises in the same region and the same year outside of this enterprise is used as the instrumental variable (IV) for individual digital transformation. The results are shown in Table 7 below. The Kleibergen-Paap rk LM statistic has a p-value of 0, which significantly rejects the original hypothesis that the instrumental variables are unidentifiable. The Cragg-Donald Wald F-statistic (192.307) is greater than the critical value of Stock-Yogo weak instrumental variable at 10% significance level (16.38), rejecting the original hypothesis of weak instrumental variables. Therefore, the instrumental variables selected in this paper are valid. Based on the results in column (2) of Table 7, the coefficient of digital transformation is significantly positive at the 1% level, implying the conclusion that digital transformation improves the performance of automobile manufacturing enterprises still holds.

Table 7: The results of the endogeneity test (Instrumental variable method)

	(1)	(2)
	DT	**ROA**
	Phase I	**Phase II**
IV	0.9845^{***}	
	(10.88)	
DT		0.3536^{***}
		(3.23)
Constant	-0.1892^{**}	-0.2343^{*}
	(-1.94)	(-1.68)
Control variables	YES	YES
Year	YES	YES
Individual	YES	YES
N	726	726
R^2	0.4837	0.3184
Kleibergen-Paap rk LM statistic		43.658
		[0.000]
Cragg-Donald Wald F statistic		192.307
		{16.38}

Note: Values in ( ) are z-values, values in [ ] are p-values, and values in { } are critical values at the 10% significance level for the Stock-Yogo weak instrumental variable

Moreover, this paper uses the Heckman two-step method for endogeneity testing. In the first step, a dummy variable for digital transformation (Dum_DT) is constructed, assigning a value of 1 if the enterprise carries out digital transformation and 0 otherwise. Then the Inverse Mills Ratio (IMR) is obtained through regression. In the second step, the IMR is added as a control variable to the original model, and the regression results are obtained as shown in column (2) of Table 8. The coefficient of the IMR is -0.0298, but it does not pass the significance test, which means that there is no bias in the sample selection of this paper. Therefore, the regression results of the benchmark model in this paper are reliable.

Table 8: The results of the endogeneity test (Heckman two-step estimation)

	(1)	(2)
	Dum_DT	**ROA**
	Selection model	The second step
DT		0.1089^{**}
		(2.43)
IMR		-0.0298
		(-1.42)
		(3.82)
Control	YES	YES
Year	YES	YES
Individual	YES	YES
N	726	726

5.2.3 Analysis of long-term effect

In the short term, digital transformation enables enterprises to optimize localized business processes. In the long term, through digital transformation, enterprises can accomplish comprehensive and systematic organizational change that affects their long-term performance. Therefore, this paper explores the long-term impact of digital transformation on the performance of automobile manufacturing enterprises in China and the results are shown in Table 9 below.

The coefficients of digital transformation in both the one and two-phase lag models are significantly positive, meaning that the impact of digital transformation on the performance of automobile manufacturing enterprises is long-term and there is a certain lag effect. Moreover, the coefficient of digital transformation in the one-phase lag model is larger than that in the current model, indicating that the positive impact of digital transformation on enterprise performance is greater in the second year than in the current year.

Table 9: The results of long-term effect

	(1)	**(2)**	**(3)**
	Current model	**One-phase lag model**	**Two-phase lag model**
DT	0.1096^{***}	0.1316^{**}	0.0965^{**}
	(3.72)	(2.06)	(2.05)
Constant	-0.3282^{**}	-0.4968^{***}	-0.4842^{*}
	(-2.08)	(-2.84)	(-1.76)
Control variables	YES	YES	YES
Year	YES	YES	YES
Individual	YES	YES	YES
N	726	660	594
R^2	0.3456	0.1355	0.1011
R^2_a	0.3309	0.1154	0.0794
F	5.8265^{***}	6.0649^{***}	4.5420^{***}

5.2.4 Heterogeneity analysis

(1) Heterogeneity analysis of enterprise ownership

Based on the coding of the ownership in the CSMAR database, automobile manufacturing enterprises are classified into two groups firstly: state-owned enterprises and non-state-owned enterprises. The regression results of the two groups are shown in columns (1) and (2) of Table 10 below.

The coefficient of the digital transformation in column (2) is significantly positive at the 5% level, which implies that digital transformation enhances the performance of non-state-owned automobile manufacturing enterprises. Although the digital transformation coefficient in column (1) is also positive, it does not pass the significance test. Theoretically, on the one hand, non-state-owned enterprises are more innovative and pioneering than state-owned enterprises, and can better infiltrate digital technology into physical projects, which helps them to carry out the transformation of organizational management and business processes and achieve higher levels of performance. On the other hand, non-state-owned enterprises are less constrained by policy, which gives them a high degree of autonomy and enables them to make bold digital changes to generate higher revenues.

(2) Heterogeneity analysis of enterprise scale

Secondly, based on the median of total assets, automobile manufacturing enterprises are classified into two groups: large-scale enterprises and small and medium-sized enterprises (SMEs). The results of the regression are shown in columns (3) and (4) of Table 10 below.

The coefficient of the digital transformation in column (4) is 0.1010, which passes the significance test at the 1% level. It can be concluded that digital transformation has a significant positive impact on the performance level of small and medium-sized automobile manufacturing enterprises in China. However, the results in column (3) show that the impact of digital transformation on the performance of large-scale automobile manufacturing enterprises is not significant. Generally speaking, compared with large-scale enterprises, small and medium-sized automobile manufacturing enterprises have more streamlined internal management processes, which gives them higher decision-making flexibility and operational efficiency to maximize the release of digital dividends and hence performance.

(3) Heterogeneity analysis of enterprise region

Thirdly, considering the sample size of this paper, automobile manufacturing enterprises in China are divided into two groups: enterprises in the eastern region and enterprises in the non-eastern region. The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan; the non-eastern region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Jilin, Heilongjiang, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The regression results of the two groups are shown in columns (5) and (6) of Table 10.

The coefficient of digital transformation in Column (5) is 0.1258, which is significant at the 1% level. So it can be concluded that digital transformation contributes to the improvement of the performance of automobile manufacturing enterprises in the eastern region. By analyzing the results in Column (6), it is found that digital transformation does not have a significant effect on the performance of automobile manufacturing enterprises in the non-eastern region. There are two possible reasons for this result. On the one hand, the high level of economic development, the developed digital infrastructure and the fast pace of digital technology research and development in the eastern region lay the foundation for enterprises to implement digital transformation strategies. In addition, there are several universities and research institutes in the eastern region, making it possible to gather digital talent. On the other hand, the eastern region has an advantage in terms of the policy environment for digital transformation. In recent years, a large number of policies related to the digital economy have been enacted in the eastern region, resulting in an increase in the overall level of digital economy development in the region. Moreover, digital pilot projects are concentrated in eastern regions such as Beijing, Tianjin and Hebei, which will further enhance the development of the digital economy in the eastern region and accelerate the process of enterprise digital transformation.

Table 10: Results of the heterogeneity test

	(1)	(2)	(3)	(4)	(5)	(6)
	State-owned	**Non-state-owned**	**Large scale**	**Small and medium-sized**	**Eastern region**	**Non-eastern region**
DT	0.0434	0.0970**	0.1185	0.1010***	0.1258***	0.1550
	(1.25)	(2.06)	(1.60)	(3.21)	(3.98)	(1.65)
Constant	-0.7102***	-0.8438**	-1.4579***	-0.5962*	-0.5507***	-0.5529
	(-4.36)	(-2.56)	(-3.22)	(-1.79)	(-3.11)	(-1.69)
Control variables	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES
N	319	407	363	363	484	242
R^2	0.3151	0.4696	0.4786	0.2170	0.3306	0.4464
R^2_a	0.2788	0.4478	0.4545	0.1808	0.3077	0.4070
F	15.2038***	4.7611***	5.8510***	5.8188***	7.3782***	6.2226***

5.3 Mechanism test results and analysis

5.3.1 Results analysis

The results of the mechanism test are shown in Table 11 below. Column (1) in Table 11 shows the regression results of digital transformation on the performance of automobile manufacturing enterprises in China, which proves that digital transformation can significantly improve enterprise performance. Column (2) shows the results of a regression with human capital as the dependent variable and digital transformation of automobile manufacturing enterprises as the independent variable. The coefficient of digital transformation in column (2) is 0.1523, which is significant at the 5% level, implying that the digital transformation of automobile manufacturing enterprises improves the level of enterprise human capital. Based on the mechanism analysis in the previous section, an increase in the level of human capital has a positive impact on the performance of enterprises. Specifically, human capital is a valuable resource that enables the enterprise to sustainably gain competitive advantages and higher profits. In summary, human capital can be considered as a mechanism by which digital transformation affects the performance of automobile manufacturing enterprises in China, and hypothesis 2 above is confirmed.

Table 11: Mechanism Test Results

	(1)	(2)
	ROA	**Hc**
DT	0.1096***	0.1523**
	(3.72)	(2.08)
Constant	-0.3282**	0.0164
	(-2.08)	(0.10)
Control variables	YES	YES
Year	YES	YES
Individual	YES	YES
N	726	726
R^2	0.3456	0.1836
R^2_a	0.3309	0.1652
F	5.8265***	7.2433***

5.3.2 Robustness Tests

Similarly, the robustness test of the mechanism is conducted and the results are shown in Table 12 below. The results in column (2) show that the coefficient of digital transformation is 0.1624, which is significant at the 1% level and consistent with the results of this paper above, implying that the mechanism of enterprise human capital is reliable.

Table 12: Robustness test results of mechanism test

	(1)	(2)
	ROA	**Hc**
DT	0.1385***	0.1624***
	(3.78)	(3.22)
Constant	-0.7732***	0.1758
	(-3.17)	(0.93)
Control variables	YES	YES
Year	YES	YES
Individual	YES	YES
N	594	594
R^2	0.3734	0.2268
R^2_a	0.3583	0.2081
F	5.5255***	7.0983***

5.4 Moderating effects test results and analyses

5.4.1 Results analysis

The results of the moderating effects test are shown in Table 13 below. The variables c_DT, c_BC and c_DC are new variables obtained from the decentralization of digital transformation (DT), business capacity (BC) and development capacity (DC) respectively. The variables c_DT*c_Bc and c_DT*c_DC are the interaction terms of the new variables.

This paper analyses the moderating effect of enterprise business capacity first. The results in column (1) show that the adjusted R^2 of the model is 0.4112. Column (2) adds the interaction term between digital transformation and the business capacity of enterprises (c_DT*c_Bc) based on the model in column (1). The value of adjusted R^2 is 0.4194 in column (2), which is higher than the value in column (1), confirming the existence of the moderating effect of business capacity. In addition, the coefficient of the interaction term (c_DT*c_Bc) is significant at the 5% level, which also proves the moderating effect of enterprise business capacity.

It should be clear that the proxy variable of enterprise business capacity selected in this paper is a reverse indicator, and the larger the value, the weaker the enterprise business capacity. Specifically, the results in column (1) and column (2) show that the regression coefficient of the interaction term is -0.4414 and the coefficients of digital transformation are all significantly positive, so it can be concluded that inadequate business capacity weakens the positive impact of digital transformation on the performance of automobile manufacturing enterprises. In other words, weaker business capacity plays a negative moderating role in the effect of digital transformation on the performance of automobile manufacturing enterprises. In addition, the coefficient of digital transformation decreases from 0.0822 in column (1) to 0.0819 in column (2), meaning that the positive effect of digital transformation on enterprise performance is diminished. To sum up, hypothesis 4 is verified.

Table 13: Moderating Effects Test Results

	(1)	(2)	(3)	(4)
	ROA	**ROA**	**ROA**	**ROA**
c_DT	0.0822***	0.0819**	0.1049***	0.1188***
	(2.91)	(2.23)	(3.72)	(4.04)
c_Bc	-0.0953***	-0.0987***		
	(-5.92)	(-6.27)		
c_Dc			0.0240**	0.0387***
			(2.11)	(4.58)
c_DT*c_Bc		-0.4414**		
		(-2.28)		
c_DT*c_Dc				0.5618**
				(2.44)
Constant	-0.1776	-0.2278*	-0.2003	-0.1806
	(-1.28)	(-1.73)	(-1.04)	(-1.02)
Control variables	YES	YES	YES	YES
Year	YES	YES	YES	YES
Individual	YES	YES	YES	YES
N	726	726	726	726
R^2	0.4250	0.4338	0.3728	0.3917
R^2_a	0.4112	0.4194	0.3578	0.3762
F	11.5912***	13.6676***	7.7284***	14.2867***

Secondly, this paper analyses the moderating effect of enterprise development capacity. The results in columns (4) and (3) show that the adjusted R^2 value increases from 0.3578 to 0.3762, and the regression coefficient of the interaction term (c_DT*c_DC) is significantly positive at the 5% level. This proves the existence of the moderating effect of enterprise development capacity. Specifically, the coefficient of the interaction term (c_DT*c_DC) in column (4) is significantly positive, and the coefficient of digital transformation increases from 0.1049 in column (3) to 0.1188 in column (4), suggesting that the development capacity enhances the positive impact of digital transformation on the performance of automobile manufacturing enterprises in China. In other words, development capacity plays a positive moderating role in the effect of digital transformation on the performance of automobile manufacturing enterprises. To sum up, hypothesis 5 above is confirmed.

5.4.2 Robustness Tests

The results of the robustness tests for the moderating effects are shown in Tables 14 and 15 below. By analyzing the following two tables, it can be found that the moderating effects of the business capacity and development capacity of automobile manufacturing enterprises, although different in value, are consistent in the direction of moderation with the conclusions above, suggesting that the results of the moderating effect are reliable.

Table 14: Robustness test results of the moderating effect model (Substitution of the dependent variable)

	(1)	**(2)**	**(3)**	**(4)**
	ROE	**ROE**	**ROE**	**ROE**
c_DT	0.1828^{***}	0.1821^{**}	0.2319^{***}	0.2628^{***}
	(2.73)	(2.01)	(3.53)	(3.63)
c_Bc	-0.2033^{***}	-0.2132^{***}		
	(-5.93)	(-6.07)		
c_DT*c_Bc		-1.2866^{**}		
		(-2.36)		
c_Dc			0.0482^{**}	0.0811^{***}
			(2.14)	(3.63)
c_DT*c_Dc				1.2563^{**}
				(2.57)
Constant	-0.5190	-0.6653	-0.5824	-0.5383
	(-0.93)	(-1.27)	(-0.92)	(-0.90)
Control variables	YES	YES	YES	YES
Year	YES	YES	YES	YES
Individual	YES	YES	YES	YES
N	726	726	726	726
R^2	0.2434	0.2554	0.2027	0.2179
R^2_a	0.2252	0.2365	0.1836	0.1980
F	8.9412^{***}	8.4852^{***}	8.7902^{***}	10.2775^{***}

Table 15: Robustness test results of the moderating effect model (Adjustment of sample intervals)

	(1)	(2)	(3)	(4)
	ROA	ROA	ROA	ROA
c_DT	0.1135***	0.1108**	0.1334***	0.1500***
	(3.03)	(2.24)	(3.61)	(3.90)
c_Bc	-0.0883***	-0.0904***		
	(-6.10)	(-6.01)		
c_DT*c_Bc		-0.4840**		
		(-2.28)		
c_Dc			0.0226**	0.0376***
			(2.03)	(4.57)
c_DT*c_Dc				0.5814**
				(2.63)
Constant	-0.4322*	-0.5391**	-0.6191***	-0.5608***
	(-1.78)	(-2.35)	(-2.67)	(-2.67)
Control variables	YES	YES	YES	YES
Year	YES	YES	YES	YES
Individual	YES	YES	YES	YES
N	594	594	594	594
R^2	0.4345	0.4446	0.3993	0.4213
R^2_a	0.4198	0.4292	0.3837	0.4052
F	12.4332***	13.9547***	7.3933***	15.7699***

6. Conclusions and Insights

Based on the sample data of 66 automobile manufacturing enterprises listed in Shanghai and Shenzhen A-shares from 2012 to 2022, this paper empirically analyses the impact of digital transformation of enterprises on their performance in the automobile manufacturing industry, taking the heterogeneity effect, the mechanism effect and the moderating effect further into consideration, and obtains the following important conclusions: (1) The digital transformation can improve the performance of automobile manufacturing enterprises in China and the improvement is long-time. (2) The human capital level of enterprises is a mechanism by which digital transformation affects the performance of automobile manufacturing enterprises in China. (3) The moderating effect of enterprise capacities is significant. Specifically, the enhancement effect of digital transformation on the performance of automobile manufacturing enterprises will be diminished when the enterprise business capability is weak, and the development capacity plays a positive moderating role in the impact of digital transformation on the performance of automobile manufacturing enterprises. (4) The impact of digital transformation on enterprise performance varies by ownership, size and region. Specifically, the digital transformation improves the performance of automobile manufacturing enterprises that are non-state-owned, small and medium-sized, or located in the eastern region. Based on the conclusions above, the following recommendations are proposed.

Firstly, automobile manufacturing enterprises in China need to change their thinking, raise digital awareness, and develop differentiated digital transformation strategies. Specifically, enterprises should form a scientific cognition of digital transformation, grasp the opportunity of the era of digital technology to empower physical enterprises, and carry out digital transformation in a targeted manner in accordance with the actual situation of the enterprise. Enterprises in non-eastern regions can partner with those in eastern regions to achieve complementary advantages. In addition, large-scale enterprises should optimize their management processes to improve organizational flexibility and efficiency, so that digital transformation can bring value creation into play.

Secondly, the government should increase support for the digital transformation of automobile manufacturing enterprises and improve the policy environment for digital transformation. Specifically, the government should guide enterprises to carry out digital transformation, especially paying attention to the digital transformation of state-owned enterprises to enhance their pioneering spirit. Moreover, the government needs to actively promote the construction of infrastructure required for the digital transformation of enterprises, such as 5G and network base stations. In addition, to cope with the problems of data leakage and infringement, the government needs to improve the corresponding laws and regulations, as well as strengthen the regulation of data elements and the protection of intellectual property rights in digital technology.

Thirdly, speeding up the cultivation of digital talents and improving the training system. The government can improve the training mode of digital talents through cooperation with universities and help enterprises introduce digital talents. From the perspective of enterprises, on the one hand, they should actively carry out staff training to help them learn the relevant knowledge of digital transformation, which in turn improves the overall quality of employees. On the other hand, enterprises need to formulate a reasonable talent introduction strategy to attract digital talents at home and abroad.

Fourthly, improving the innovation capacity of enterprises and giving full play to the value-creating effects of innovation. From the perspective of enterprises, they should increase investment in R&D, strengthen industrial links based on digital technology, promote the upgrading of business models and services, and ultimately enhance their core competitiveness. Governments need to increase their support for enterprise innovation activities, such as setting up a special fund.

Finally, optimizing the allocation of resources and focusing on the building of enterprise capacity. Specifically, enterprises with strong business and development capacity should increase their investment in digital transformation. The implementation of a digital transformation strategy by an enterprise can have a "snowball" effect on the performance of the enterprise and continuously enhance its competitive advantage. For enterprises with weak business and development capacity, more attention should be paid to the improvement of their capabilities. However, these enterprises cannot give up on digital transformation altogether and can improve their capacity by adjusting the proportion of resource allocation and controlling costs.

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