Advances in Management & Applied Economics, Vol. 15, No. 2, 2025, 103-134
ISSN: 1792-7544 (print version), 1792-7552(online)
https://doi.org/10.47260/amae/1526
Scientific Press International Limited

The Impact of Digital Transformation on Total Factor Productivity of Automobile Manufacturing Enterprises in China

Shuangjie Li[1*] and Tianhui Zhang[2]

Abstract

This paper conducts a study on the impact of digital transformation on the total factor productivity (TFP) of Chinese automobile manufacturing enterprises based on the sample data of 49 enterprises listed in the Chinese automobile manufacturing a-share companies from 2012 to 2023. It is found that the digital transformation of automobile manufacturing enterprises has a significant positive impact on the improvement of their TFP level. The mechanism effect model shows that the improvement of enterprise innovation ability and the reduction of financing constraints are the mechanism paths of digital transformation to improve TFP. The moderating effect model suggests that corporate solvency plays a positive moderating role in the positive impact of digital transformation on TFP. The threshold effect model shows that the positive impact of digital transformation on TFP is non-linear. Heterogeneity analysis shows that digital transformation has a more significant positive impact on the TFP of enterprises in the four major urban agglomerations and new energy automobile enterprises. Based on the conclusions of the study, targeted policy recommendations are put forward to provide reference for automobile manufacturing enterprises to carry out digital transformation and improve TFP.

JEL classification numbers: C12, M21.
Keywords: Automobile Manufacturing, Digital Transformation, Total factor productivity of enterprises.

---

[1] Professor, Beijing University of Technology, School of Economics and Management, Beijing, China. *Corresponding author.
[2] Postgraduate, Beijing University of Technology, School of Economics and Management, Beijing, China.

Article Info: Received: January 13, 2025. Revised: February 8, 2025.
Published online: February 12, 2025.

1. Introduction

Since entering the twenty-first century, global digitization continues to develop rapidly, and digital technology has been constantly updated and iterated. At the same time, the digital economy has also become an indispensable force for China to realize high-quality development. China Academy of Information and Communication Research released “China's digital economy development research report (2024)”, pointed out that in 2023, China's digital technology innovation continued to make breakthroughs, the construction of the data factor market accelerated, the digital economy industrial system continues to improve, the total factor productivity of the digital economy has been consolidated and improved, to support China's accumulation of the new quality of productive forces to grow. In 2023, the scale of China's digital economy reached 53.9 trillion yuan, continued rapid growth since 2014, the increase is relatively stable; and since 2014, the digital economy accounted for the proportion of GDP has been increasing, in 2023, China's digital economy accounted for the proportion of GDP as high as 42.8%, the expansion of the amount of the same time, but also in the increase in efficiency. And this digital change also to the market structure, consumer demand and enterprise development has brought a profound impact, the market structure is changing rapidly, consumer demand is flexible and diverse and tends to be personalized, enterprise development is facing greater uncertainty and more intense competition.

Especially in the automobile manufacturing industry, on the one hand, the automobile manufacturing industry is the leading industry of China's economic development at this stage, and its driving effect on other industries in China, its role in promoting science and technology, as well as its stabilizing effect on the security of China's national economy are all obvious and indispensable; on the other hand, with the infiltration of digital technology, the automobile manufacturing industry has ushered in a major change: Many new automobile companies with more advanced R & D, production, operation and sales systems have entered the automobile market, which has brought greater competitive pressure to traditional automobile companies. And in recent years, new energy vehicles and intelligent connected vehicles came into being, and their proportion in the automotive market is increasing, which is also promoting the digital transformation of China's automobile manufacturing industry. Therefore, the digital transformation of automobile manufacturing enterprises is imminent and a general trend. Then, what kind of direct impact does the digital transformation of automobile manufacturing enterprises have on their total factor productivity, through what mechanism path does it realize this impact, and by what kind of factors is it moderated? Whether this effect is non-linear, these questions need to be explored in depth.

2. Literature review

The development of the digital economy has roughly gone through three stages: the information economy, the Internet economy, and the new economy (Turcan and Juho, 2014; Moulton, 2000). The focus of its connotation has also changed with the development of the digital economy. Tapscott Don (1995), the father of the digital economy, first coined the term “digital economy”, and argued that the most important component of the digital economy is e-commerce. Mesenbourg (2001) argued that the digital economy is equivalent to e-commerce, i.e., the digital economy consists of software and hardware facilities, digital network, and products traded on the Internet platform. Quah (2003) expanded the connotation of digital economy and defined digital economy as all economic activities that use the Internet to trade goods and services. Chen, et al. (2022), based on the characteristics of the current stage of the digital economy, argued that the core content of the digital economy includes digitalized information, Internet platforms, digital technologies, as well as new modes and new business forms. Therefore, domestic and foreign organizations and research institutes still have a big controversy over the statistics of digital economy, which can be mainly divided into narrow caliber and wide caliber. Enterprises, as the micro foundation of the macroeconomy, carry out digital transformation to become a necessary path for enterprise development. Some scholars at home and abroad have also studied the measurement of the degree of digital transformation of micro enterprises, but the academic community has not reached a consensus on the connotation of digital transformation. Some scholars emphasize the importance of digital technology from the perspective of enterprise transformation and upgrading. Legner, et al. (2017) believe that enterprises can be recognized as having carried out digital transformation by realizing transformation and upgrading through information technology. However, most scholars, on the basis of emphasizing digital technology, believe that digital transformation should be a process in which digital technology affects all aspects of the enterprise, highlighting the process of influencing all aspects and segments of the enterprise, such as Vial (2019), who believes that digital transformation is a process in which the application of digital technologies such as information and computing triggers changes in the properties of entities and improves the enterprise strategy and operation mode. Another part of scholars emphasize the added value brought by digital transformation from the perspective of enterprise value. For example, Han Jiaping, et al. (2022) defined digital transformation as a process in which traditional enterprises add value to their production processes and consumers by utilizing digital technologies with connectivity and analytics. While Chenyu Zhao, et al. (2021) pointed out that the degree of digital transformation is difficult to accurately measure and the lack of relevant data statistics is serious, coupled with the complexity of the mechanism of influence on the enterprise, so when measuring the degree of digital transformation of the enterprise, the vast majority of studies did not look deeply into the connotation of digital transformation, or even measure the degree of digital transformation of the enterprise from a single dimension. For example, Wu Fei, et al. (2021) constructed a thesaurus of digital transformation features including “underlying technology application”, “technology practice application”, and conducted word frequency counts on the disclosure of relevant keywords in the annual reports of the enterprises, so as to portray the digital transformation of the enterprises. In addition, Huang Bo, et al. (2023) and Luo Jia, et al. (2023), in measuring the degree of micro-digital transformation, consider that the data disclosed in the annual reports of enterprises are highly subjective, and choose the number of digital patents applied for or granted to measure the level of digital technological innovation as an alternative to the measurement of the degree of digital transformation.

Total factor productivity (TFP) is an important indicator of economic development potential, reflecting the nature of productivity as an economic concept. As early as 1957, Robert Solow put forward the concept of total factor productivity: the portion of output growth that cannot be explained by factor inputs such as labor, capital, etc., and later scholars also referred to total factor productivity as “Solow's surplus” (Aigener, et al., 1977). For the connotation of total factor productivity, early scholars decomposed the connotation of enterprise total factor productivity into technical efficiency and scale efficiency, and attributed the growth of enterprise total factor productivity to technological progress (Fare, et al., 1994), and the depth of the study, the connotation of enterprise total factor productivity has been continuously expanded, and it is regarded as a comprehensive indicator that can comprehensively assess the impact of innovation, management, production and external environment on the efficiency of enterprise output efficiency (Syverson, 2011).

Many scholars conduct quantitative research on total factor productivity in related studies, and scholars' approaches to measuring total factor productivity can be broadly categorized into the following two types: the first type is non-frontier analysis, which mainly includes the growth accounting method, growth rate regression method, and the proxy variable method; the second type is frontier analysis, which includes Data Envelopment Analysis (DEA), a deterministic method, and Stochastic Frontier Analysis (SFA), a parametric method (Banker et al., 1984). Solow firstly proposed the growth accounting method, he decomposed the growth of firms' output into the growth of factor inputs of labor and capital plus the growth of residual value, which is the total factor productivity. However, this method underestimates the contribution of labor and capital to output because it equates residual growth with technological growth. On this basis, Jorgenson and Griliches (1967) separated out output growth due to improvements in the quality of factor inputs and overcame the limitations of the assumption that labor is homogeneous and uses the capital stock. The data envelopment analysis method is flawed because it does not take into account the stochastic factor when calculating the deviation of production technology from the frontier of the firm; however, the stochastic frontier method reduces the measurement bias because it can decompose total factor productivity into unproductive efficiency and stochastic perturbation components. However, Lu Xiaodong and Lian Yujun (2012) pointed out that it should be distinguished whether the dimension is a macro or micro approach, and the macro productivity level cannot be simply understood as a linear summation of micro productivity (Bluudell, et al., 1998). In response to the simultaneity bias and sample selectivity bias in the estimation process of enterprise total factor productivity, many scholars have proposed corrective solutions, such as parametric and semiparametric methods, such as the least squares method, the fixed-effects method, the OP method, and the LP method, and found that the semiparametric method can well solve the endogeneity and sample selectivity problems in the traditional measurement methods, and thus the OP method and the LP method have gradually become the Therefore, OP method and LP method have gradually become the mainstream methods to measure the total factor productivity of enterprises.

Digital economy and digital transformation will affect total factor productivity to a large extent, but there are differences in the conclusions of the impact of digital economy and digital transformation on total factor productivity. Most scholars have found that the digital economy and digital transformation will significantly increase total factor productivity. For example, Guo Jinhua, et al. (2021) takes the "Broadband China" strategy as an exogenous shock and conducts a quasi-natural experiment, which shows that the construction of digital infrastructure can enhance total factor productivity by replacing human capital and other paths; Guo Feng, et al. (2022) show that the digital economy can reduce the cost of production and liquidity risk of enterprises and thus Liu Fei, (2020) found that the application of digital technology and the transformation of digital business models will bring about the growth of digital factor inputs, which can directly improve the total factor productivity of enterprises and can also be complemented with human and capital factors to indirectly promote the improvement of the total factor level of enterprises. Wen, et al. (2022) and Ren, et al. (2022) argue that firms undergoing digital transformation can increase firms' total factor productivity by reducing transaction costs and improving operational efficiency. And Bai Wanping (2022) argues that the digital economy can increase total factor productivity by expanding the size of the technology market, but this positive impact is characterized by diminishing marginal returns. In addition, many internal and external factors are influencing factors of total factor productivity, Tello (2015) and Wulichao, et al. (2021) found through their studies that process innovation and improving the quality of enterprise scientific and technological research and development will increase the total factor productivity of the enterprise, respectively. Wang Bing and Yan Pengfei (2007) introduced environmental factors into the model to correct the existing total factor productivity and pointed out that the environmental factors have a positive impact on the total factor productivity. Hong Herb, et al. (2021) found that in the short term, industrial policy reduces firms' total factor productivity by exacerbating firms' cost years, but in the long term, it enhances firms' ability to acquire resources and increases total factor productivity. These differences in both internal and external factors affect the effect of digital transformation on total factor productivity.

First, the combing of relevant research by scholars at home and abroad in this paper reveals that there are still problems to be further studied, which points out the direction for the research of this paper. First, the existing literature on the connotation, influencing factors, paths and economic consequences of digital transformation has been relatively rich, laying a solid foundation for the research of this paper. Most of the articles that study the impact of digital transformation on the level of total factor productivity are mostly focused on the overall regional data or a code industry data for research; the literature that selects enterprise-level data for research is less, and most of them are focused on the study of manufacturing enterprises. Few articles focus their research on China's automobile manufacturing enterprises.

Second, the existing research articles on enterprise digital transformation, the measurement of digital transformation is mostly focused on the theoretical level, qualitative level, although the theoretical research is constantly enriching, the evaluation method also takes into account the impact of multiple factors, and from a single indicator to build a multi-dimensional indicator system; but the research on measuring digital transformation by quantitative methods is insufficient, and the measurement method has not reached agreement, and most of the use of quantitative methods to measure digital transformation. Most of the articles measuring digital transformation only consider the word frequency of digital transformation-related words in the annual report, and it is difficult to avoid the problem that enterprises only deliberately present a high level of digital transformation in the annual report, but the actual digital transformation has not really landed.

Third, in terms of the mechanism path and regulating variables of digital transformation affecting the total factor productivity level of enterprises, the research on the mechanism path mainly focuses on technological innovation and various efficiencies, and pays less attention to financing constraints.

Fourth, in the existing articles that study the economic consequences of digital transformation, the research conclusions have not yet reached a consensus. Most scholars believe that the impact of digital transformation is positive and linear, but some scholars consider the different stages of digital transformation or the selected research objects in their research, and believe that digital transformation will produce negative or positive but non-linear economic consequences at a certain stage. Therefore, what kind of economic consequences digital transformation will bring, and what kind of impact it will have on the automobile manufacturing enterprises to go by factor productivity deserves in-depth research.

3. Theoretical analysis and research assumptions

3.1 The impact of digital transformation on the total factor productivity of Chinese automobile manufacturing enterprises

The digital economy has brought more data and new digital technologies; data, as a new factor of production, has permeated all aspects of value creation and value capture in enterprises; and digital technologies have brought a new paradigm for production and operation, thereby reducing various costs for enterprises. According to the endogenous growth theory, the digital economy helps to promote total factor productivity. In the R&D segment, the introduction of digital technology in the R&D segment will largely improve the efficiency of enterprise R&D. On the one hand, the use of big data and other digital technologies by enterprises makes it possible for them to avoid information asymmetry, quickly obtain a large amount of market data, accurately understand market trends and changes in consumer preferences, and promote targeted innovation from market demand; on the other hand, the use of digital technologies allows enterprises to use virtual testing, simulation and verification instead of the traditional manual experiments in the R & D process, reducing costs and Reduce the impact of human factors on the experimental results. In the production process, on the one hand, enterprises use big data, cloud platforms and other digital means in the production process, not only can adjust the production plan in a timely manner according to changes in consumer demand, improve the ability to provide consumers with personalized customized services, and achieve flexible production; and marketing, inventory and other data can be real-time feedback to the production department, timely planning adjustments, intelligent scheduling, and improve resource allocation efficiency. On the On the other hand, the introduction of automated production lines will largely improve production efficiency and product quality, while replacing human capital and reducing production costs. In marketing, digital technology makes the enterprise marketing department can not only timely access to internal production and inventory data, according to the production and inventory situation to adjust the marketing strategy; and can be more accurate access to the market and consumer demand information, so that the enterprise in the marketing process to accurately reach the market demand and consumer personalized to the demand and enhance customer stickiness management, data to assist marketing decisions. In the operation link. When R & D, production, sales and other aspects of internal digital transformation to a certain extent, enterprises need to formulate a digital transformation strategy at the top design level, so that data can be circulated in the whole process, the whole business. This also requires enterprises to break down the barriers between the various links of the operation process and open up the closed loop of data collection, analysis and application in each link.

Therefore, digital transformation is considered to have a positive impact on total factor productivity improvement. Based on the above analysis, this paper proposes the following hypotheses:

Hypothesis 1: Digital transformation has a positive impact on total factor productivity improvement in automobile manufacturing enterprises and there is no Solow's paradox.

3.2 The influence mechanism of digital transformation on total factor productivity of Chinese automobile manufacturing enterprises

According to Schumpeter's theory of innovation, the role of “creative destruction” played by research and development activities promotes technological progress, which in turn promotes the endogenous growth of the economy. After the economy has entered the new normal, the mode of economic development has changed from relying on the demographic dividend and external demand to relying on technological innovation and the quality of workers. The development of the digital economy has brought a large number of new technologies, which has prompted the enterprises and economic subjects to continuously carry out the application and innovation of digital technology and continuously improve the innovation ability. The improvement of innovation capacity brought about by digital transformation allows enterprises to more widely apply digital technologies such as big data, cloud platforms, and the Internet of Things to realize the digitization of various processes. This promotes enterprises to improve R&D capabilities, shorten the R&D cycle, ensure rapid product updating and iteration, meet the diversified and personalized needs of consumers, and enhance the competitiveness of enterprises; and is conducive to improving the production efficiency, operational efficiency, and sales efficiency of the automobile manufacturing enterprises, which in turn improves the total factor productivity of enterprises. Based on the above analysis, this paper puts forward the following hypothesis:

Hypothesis 2: Digital transformation can enhance the total factor productivity of automobile manufacturing enterprises by improving innovation ability.

The development of the digital economy for the development of automobile manufacturing enterprises to carry out digital economic empowerment, provide more effective data information, provide intelligent, digital platform, which can improve enterprise transparency, optimize the management of funds and risk control, and retain the enterprise production, transaction and other data and thus provide a more accurate credit assessment, which makes financial institutions to reduce the threshold of investment, and provide more capital for the enterprise Support. Moreover, digital transformation enables enterprises to obtain more financing channels and information, improves the matching efficiency with investors, and reduces financing costs. The reduction of the level of financing constraints for enterprise production, technological innovation, etc. to provide more financial support, is conducive to supporting enterprises to increase investment, especially for the automobile manufacturing enterprises in the production and R & D and other aspects of the need for greater capital investment, the decline in the level of financing constraints is conducive to further enhance the competitiveness of the market and the ability of sustainable development, and to improve the total factor productivity. Based on the above analysis, this paper puts forward the following hypothesis:

Hypothesis 3: Digital transformation can improve total factor productivity of automobile manufacturing enterprises by reducing the level of financing constraints faced by enterprises.

3.3 Moderating effect of digital transformation on total factor productivity of Chinese automobile manufacturing enterprise

Solvency refers to the ability of an enterprise to repay its debts with existing resources within a certain period of time, which is used to measure the ability of an enterprise to repay principal and interest on time. Solvency plays a crucial role in financial health and sustainable development because it directly affects the cost of financing and credit rating of enterprises. The digital economy empowers enterprises to develop and enhances their solvency, thereby improving their capital structure and cash flow by reducing financing costs, enhancing financial stability and profitability, and promoting the improvement of total factor productivity. Moreover, in the context of digital economy, the types and complexity of risks faced by enterprises will be greater, and the degree of competition will also be greater. Especially for automobile manufacturing enterprises that require large capital investment and are difficult to obtain returns in the short term, better debt repayment ability can promote the improvement of total factor productivity of automobile manufacturing enterprises in the context of digital economy. Based on the above analysis, this paper proposes the following hypothesis:

Hypothesis 4: Debt service capacity plays a positive moderating role in the relationship of digital transformation on total factor productivity of automobile manufacturing enterprises.

3.4 Nonlinear impact of digital transformation on total factor productivity of Chinese automobile manufacturing firms

Consider Metcalfe's law and the fact that the digital economy is characterized by technology diffusion and network effects. With the gradual adoption of digital technologies in the automotive industry, the initial marginal benefits may be low because companies need to invest a lot of resources in infrastructure construction, staff training and technology development. However, when digital technologies reach a certain level of popularity and maturity, technology diffusion and network effects begin to emerge. For example, IoT technology may only be used for part of the automotive manufacturing process at the beginning, but as the technology becomes more widely used and standardized, the entire production system can be seamlessly connected, and the efficiency of data sharing and collaborative work increases dramatically. This effect has led to an increasing trend in the marginal returns from each new unit of digital technology investment, driving the industry's high-quality development. In addition, the economies of scale and economies of scope effects brought about by the digital economy are also important reasons for the marginal increment. Digital transformation enables automotive manufacturing companies to achieve larger scale production and broader product lines through digital platforms and smart manufacturing technologies. This economy of scale and economy of scope effect makes the overall operational efficiency and market competitiveness of the enterprise significantly improve with each additional unit of digital technology input, with increasing marginal returns, thus increasing total factor productivity. Based on the above analysis, this paper proposes the following hypothesis:

Hypothesis 5: There is a nonlinear characteristic in the effect of digital transformation on total factor productivity of automobile manufacturing enterprises.

4. Research Design

4.1 Sample selection and data sources

This paper takes listed companies in China's automobile manufacturing industry as the research scope. Referring to the “Guidelines on Industry Classification of Listed Companies (2012 Revision)” of the China Securities Regulatory Commission, the automobile manufacturing companies listed on China's A-share market from 2012 to 2023 are selected as the research objects. In order to ensure the reliability of the research results, the research objects are further screened: (1) excluding companies listed in IPOs between 2012-2023 and those that have been delisted; (2) excluding listed companies related to the financial industry; (3) excluding ST and *ST listed companies that are poorly operated; and (4) excluding listed companies that have more serious missing data. After finishing, this paper finally determines that the research object covers 49 listed companies; a total of 588 observations.

The data of listed companies in this paper mainly come from Cathay Pacific database and Wind database, and some of the missing data are collated and calculated with the help of annual reports of listed companies, social responsibility reports, and Juchao Information Network or made up by interpolation; the data at the inter-provincial level mainly come from China Statistical Yearbook and statistical yearbooks of provinces and cities, and some of the missing data are made up by interpolation. In this paper, to eliminate the influence of extreme values, the data are reduced by 1%.

4.2 Explanation of variables

4.2.1 Explained variables

The explained variable selected in this paper is total factor productivity (TFP). Many scholars have proposed a variety of correction schemes for the problems of simultaneity bias and sample selection bias in the measurement process of microenterprise total factor productivity, such as the parametric and semiparametric methods such as the least squares method, the fixed effects method, the OP method, the LP method and the GMM method. And it is found that the least squares method and the fixed effects method are not sufficient to solve the endogeneity problem; the GMM method requires a long time span of the sample; and the LP method can better solve the endogeneity problem caused by dealing with the mutual decision bias of the sample data and the bias problem caused by the sample selection bias. In summary, the LP method is chosen to measure the total factor productivity of enterprises in this study. The input indicators and output indicators are as follows, as shown in Table 1:

Input indicators: (1) capital input: net fixed assets; (2) labor input: number of employees; (3) intermediate inputs

Output indicators: operating income

The data of total factor productivity (TFP) is finally obtained, and the larger the index is, the higher the level of total factor productivity is.

Table 1: Measuring index and method of total factor productivity

Variables	Measurement method
Total factor productivity (TFP)	OP method, LP method Input variables: Capital inputs: net fixed assets Labor inputs: number of employees Intermediate inputs Output variables: Operating income

4.2.2 Explanatory variables

The explanatory variable chosen in this paper is digital transformation. The current literature has the following main methods for measuring digital transformation: when measuring micro digital transformation, the first thing is to construct a binary variable of digital transformation, if the enterprise is undergoing digital transformation, it takes 1, and if it is not, it takes 0 (He Fan and Liu Hongxia, 2019), which is a more intuitive method but cannot characterize the degree of digital transformation carried out by the enterprise more accurately. Second, the method of text mining is used to extract the corresponding text from the annual reports of enterprises to construct the indicator system, such as Zhao Chenyu et al. (2021) constructed the indicator system from the four dimensions of digital technology application, Internet business model, intelligent manufacturing, and modern information system, which is a more comprehensive method to measure the dimensions, but there is a strong subjectivity in the data disclosed in the annual reports of enterprises. Third, choose an indicator to measure a perspective of digitalization and then characterize the digital transformation, such as Huang Bo (2023) used digital patents to characterize digital technological innovation, the method of measurement of a single dimension, but the digital patents to avoid the subjectivity of the information disclosed in the annual report . In summary, this paper constructs digital transformation measurement index system, but in the construction of the index system, not only consider the disclosure of the relevant text in the annual report of the enterprise also consider the authorization of digital economy patents, as shown in Table 5-2. When measuring the total number of key words about enterprise digital transformation in the annual reports of automobile manufacturing enterprises, the text mining method is used, with reference to the study of Wu Fei, et al. (2021), which constructs the digital belonging dictionary from the five dimensions of artificial intelligence technology, big data technology, cloud computing technology, blockchain technology and the use of digital technology, and carries out a textual analysis of the relevant segments in the annual reports. The number of digital patent grants is obtained by matching the patent main classification number issued by the State Intellectual Property Office with the Statistical Classification of Digital Economy and Its Core Industries issued by the National Bureau of Statistics in 2021. And then calculate the total number of word frequencies of each dimension in the annual report of the enterprise, and then use the entropy value method and equal weight method to determine the weight of the two indicators, and finally get the data of digital transformation (DIG), the larger the index, the higher the level of development of the digital economy. Among them, the digital transformation data measured by the entropy method is used in the benchmark regression model, mechanism effect model, moderating effect model, threshold effect model, and the digital transformation data measured by the equal weight method is used in the robustness test.

Table 2: Digital transformation index system

Variables	Indicator system
Digital transformation (DIG)	Total number of keywords for digital transformation in annual reports of automotive manufacturing companies
	Number of digital economy patents granted to automotive manufacturing companies

4.2.3 Institutional variables

1) Innovation capacity

This paper uses innovation capacity as a mechanism variable to study the impact of digital transformation on total factor productivity. Checking the existing literature, there are two main types of ways to measure corporate innovation: the first type is the innovation output perspective, such as Li and Zheng (2016) who use the number of patents to measure the innovative capacity of enterprises. The second type is the R&D investment perspective, such as Hu Guoliu, et al. (2019) use the ratio of R&D investment to operating income to measure innovation capability. In this paper, we consider that the number of patents is the most direct embodiment of innovation capacity, and the number of authorizations can more realistically respond to innovation output, but innovation efficiency is more comparable. Therefore, this paper chooses the ratio of the number of patents granted plus logarithm to the R&D expenditure plus logarithm to measure innovation ability (INN).

2) Financing constraints

This paper uses financing constraint as a mechanism variable to study the impact of digital transformation on total factor productivity. The level of financing constraint reflects the difficulty of obtaining external financial support in the capital market, and a lower level of financing constraint implies that it is easier for enterprises to obtain financing at a lower cost. There are four main measures of financing constraints, namely KZ index, WW index, SA index and FC index, and this paper chooses SA index to measure the level of enterprise financing constraints. The larger the index, the smaller the financing constraint faced by the enterprise.

4.2.4 Moderating variables

This paper investigates the difference in the impact of digital transformation on total factor productivity under different solvency scenarios. It is an important means to enhance financial stability, improve cash flow management and broaden financing channels for enterprises to improve their solvency, and this paper uses the current ratio to measure the debt service (DP) of enterprises.

4.2.5 Threshold variables

Operating profit margin is one of the key financial indicators of an enterprise, measuring the ability of an enterprise to generate profits from its daily business activities after deducting operating costs and taxes. This indicator helps to assess the financial health of a firm and the effectiveness of its strategy execution, and is an indicator that investors and bondholders pay more attention to. The higher the operating profit margin, the stronger the enterprise's ability to earn profits through its main business, and also represents the enterprise's higher operating efficiency and profitability. This paper adopts the operating profit divided by operating income to measure the operating profit margin.

4.2.6 Control variables

The level of total factor productivity is not only affected by the digital transformation, but also by many other factors, in order to try to avoid the estimation bias due to the model setup, referring to the relevant studies, the number of digital economy enterprises in the province where the enterprise is located (DIG-NUM), the financial support of the province where the enterprise is located (FIN), the level of informatization of the province where the enterprise is located (INF), the level of industrialization of the province where the enterprise is located (IND), shareholding concentration (SHARE), registered capital level (REG), years of listing (AGE), and gearing ratio (LEV) are used as control variables, and year fixed effects and individual fixed effects are added to the regression model.

All the variables involved in this paper are shown in Table 3.

Table 3: Variable description

Variable Type	Variable name	Variable symbol	Variable Definition
Explanatory variable	Total factor productivity	TFP	Measured using the OP method
Interpretation Variables	Digital Transformation	DIG	Measured using the entropy method
Mechanisms Variables	Innovation capacity	INN	ln(1+number of patents granted)/ln(1+R&D investment)*100
	Financing constraints	SA	-0.737*Natural logarithm of firm's total asset size + 0.043*(Square of natural logarithm of firm's total asset size) - 0.040*Firm's operating year
Moderator variable	Debt-paying ability	DP	Current ratio = current assets/current liabilities * 100
Threshold variables	Operating profit margin	OM	Operating profit/operating income*100
Control Variables	Number of digital economy enterprises in the province where the enterprise is located	DIG-NUM	Number of digital economy enterprises in the province where the enterprise is located
	Financial support from the province where the enterprise is located	FIN	Fiscal general budget expenditures/Gross Regional Product*100
	Informatization level of the province where the enterprise is located	INF	Total postal and telecommunication business/gross regional product*100
	Level of industrialization in the province where the enterprise is located	IND	Value added of industry/gross regional product*100
	Shareholding concentration	SHARE	Sum of shareholdings of the top 10 largest shareholders
	Level of registered capital	REG	The registered capital of an enterprise is taken as a logarithm
	Number of years listed	AGE	Number of years the enterprise has been listed
	Asset-liability ratio	LEV	Total liabilities/total assets*100

4.3 Modeling

4.3.1 Benchmark regression model

Hausman test shows that the P-value is 0.000, which can more strongly reject the original hypothesis that the individual disturbance term is not correlated with the explanatory variables, and choose the fixed effect model. And considering that the sample selected in this paper is the panel data of 49 A-share listed automobile manufacturing enterprises from 2012-2023, there may be large differences among enterprises; and with the development of time, the level of total factor productivity will also be affected. Therefore, this paper believes that it is more reasonable to establish a time-individual two-way fixed effects model. This paper constructs the following benchmark regression model to study the direct impact of digital transformation on the total factor productivity of China's A-share automobile manufacturing enterprises.

$$\mathrm{TFP_{it}} = \alpha_0 + \alpha_1 \mathrm{DIG_{it}} + \alpha \mathrm{CONTROL_{it}} + \varepsilon_i + \phi_t + e_{it} \tag{1}$$

Where, $\mathrm{TFP_{it}}$ denotes the total factor productivity level of automobile manufacturing firms in the year; $\mathrm{DIG_{it}}$ denotes the degree of digital transformation of automobile manufacturing firms in the year; $\mathrm{CONTROL_{it}}$ denotes the control variable; ε_i is the individual fixed effect; ϕ_t is the time fixed effect; and e_{it} denotes the random perturbation term.

4.3.2 Mechanism testing model

This paper studies the mechanism path of digital transformation on the total factor productivity of 49 A-share listed automobile manufacturing enterprises in China from the aspects of innovation ability and financing constraints, and constructs the following mechanism testing model.

$$\mathrm{CE_{it}} = \beta_0 + \beta_1 \mathrm{DIG_{it}} + \beta \mathrm{CONTROL_{it}} + e_{it} + \varepsilon_i + \phi_t \tag{2}$$

$$\mathrm{SA_{it}} = \gamma_0 + \gamma_1 \mathrm{DIG_{it}} + \gamma \mathrm{CONTROL_{it}} + e_{it} + \varepsilon_i + \phi_t \tag{3}$$

Where, $\mathrm{CE_{it}}$ denotes the innovation capacity of automobile manufacturing firms in the year; $\mathrm{SA_{it}}$ represents the level of financing constraints faced by automobile manufacturing enterprises in the year.

If β_1 and γ_1 are significant, it indicates that digital transformation significantly affects total factor productivity and the influence of innovation ability and financing constraints on total factor productivity is obvious, which further indicates that innovation ability and financing constraints can be used as the mechanism path of digital transformation affecting total factor productivity.

4.3.3 Moderated effects model

Based on the baseline regression model, the moderating variable, i.e., the interaction term between solvency and the core explanatory variable after digital transformation decentralization, is introduced to construct the moderating effect model.

$$\mathrm{TFP}_{it} = \delta_0 + \delta_1 \mathrm{DIG}_{it} + \delta_2 \mathrm{DP}_{it} + \delta_3 \mathrm{DP}_{it} * \mathrm{DIG}_{it} + \delta \mathrm{CONTROL}_{it} + e_{it} + \varepsilon_i + \phi_t \quad (4)$$

where, DP_{it} denotes the solvency of the automobile manufacturing firm in year; $\mathrm{DP}_{it} * \mathrm{DIG}_{it}$ denotes the interaction term of solvency and digital transformation; δ_3 denotes the regression coefficient of the interaction term of solvency and digital transformation.

4.3.4 Threshold effect model

In this paper, operating profit margin (OM) is selected as the threshold variable, and the single threshold model is set as follows:

$$\mathrm{TFP}_{it} = \lambda_0 + \lambda_1 \mathrm{DIG}_{it} \cdot \mathrm{I}\,(\mathrm{OM}_{it} \le a) + \lambda_2 \mathrm{DIG}_{it} \cdot \mathrm{I}(\mathrm{OM}_{it} \ge a) + \lambda \mathrm{CONTROL}_{it} + e_{it} + \varepsilon_i + \phi_t \quad (5)$$

Where ,I denotes the indicator function; OM_{it} is the threshold variable, the operating profit margin of automobile manufacturing firms in year; λ_1 is the regression coefficient when OM_{it} is less than the threshold; λ_2 is the regression coefficient when OM_{it} is greater than the threshold.

5. Analysis of empirical results

5.1 Descriptive statistics and multicollinearity test

In order to intuitively react to the distribution characteristics of the data of each variable, this paper analyzes the results of descriptive statistics for all sample variables, and the results are shown in Table 4 below.

Table 4: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
DIG	588	55.668	119.711	0	649.418
TFP	588	9.07	1.103	7.032	11.318
INN	588	5.932	7.382	0	26.604
SA	588	-3.85	.296	-4.544	-2.973
DP	588	1.568	.88	.669	6.007
OM	588	5.628	7.029	-21.508	27.687
REG	588	20.526	1.106	18.603	23.181
SHARE	588	58.661	15.825	23.87	96.75
LEV	588	50.895	16.976	13.057	94.733
AGE	588	14.235	7.042	2	29
DIG-NUM	588	146174.89	136226.86	9188.926	669068
FIN	588	17.26	5.2	10.796	35.474
INF	588	5.566	4.405	1.715	19.532
IND	588	34.839	6.36	13.871	44.73

From the perspective of the explanatory variables, the enterprise total factor productivity level is higher overall, the average value reaches 9.07, the minimum value is 7.032, the maximum value is 11.318, and there is a certain gap between the two. It shows that in terms of total factor productivity level, there is a certain gap between the listed companies in China's automobile manufacturing industry, the reason for this may be that the enterprises are located in the provinces of financial support, information technology level and the enterprise's own assets and liabilities, the length of the listing and other factors there are differences in the enterprise's ability to different, by the influence of the external conditions are also different, indicating that this paper selected samples have a stronger representativeness. From the perspective of the core explanatory variables, as a whole, the mean value of the degree of enterprise digital transformation is 55.668, indicating that most of the listed companies in China's automobile manufacturing industry are actively exploring, carrying out digital transformation and deepening; specifically, the degree of digital transformation of China's listed companies in the automobile manufacturing industry is more varied, with the maximum value of 649.418 but the minimum value of only 0, which indicates that there are Automobile manufacturing enterprises have carried out a higher degree of digital transformation and lead other enterprises in the industry, but there are also enterprises with poor ability to carry out digital transformation and have not yet carried out digital transformation.

According to the relevant theory of econometrics, it is known that when there is multicollinearity between variables, the regression model results will be affected, therefore, the multicollinearity test was conducted in this paper, and the results were shown in Table 5. The variogram inflation factor (VIF) values of each variable were all less than 5, indicating that there was no multicollinearity between the variables, that is, the regression results of the model in this paper were reliable.

Table 5: Multicollinearity test

Variables	VIF	1/VIF
DIG	2.04	0.491
INN	1.80	0.556
SA	2.29	0.436
DP	2.04	0.490
OM	1.41	0.708
REG	2.21	0.452
SHARE	1.44	0.694
AGE	3.01	0.333
LEV	2.91	0.343
DIG-NUM	1.51	0.661
FIN	2.04	0.489
INF	1.12	0.892
IND	1.76	0.569
Mean VIF		1.97

5.2 Regression results

5.2.1 Regression analysis of the digital economy on total factor productivity

Based on the econometric model, Table 6 reports the results of the benchmark regression. To enhance the robustness of the empirical results, the paper gradually adds control variables for parameter estimation based on the inclusion of core explanatory variables.

Table 6: Baseline regression result

	(1) TFP	(2) TFP	(3) TFP
DIG	0.0006*** (2.870)	0.0006*** (2.899)	0.0006*** (2.870)
DIG-NUM	0.0000*** (3.492)	0.0000*** (3.599)	0.0000*** (4.019)
REG	0.1389*** (3.018)	0.1389*** (3.035)	0.1512*** (3.327)
AGE		0.1142* (-1.858)	-0.1398** (-2.296)
IND			0.0132* (1.911)
FIN			-0.0122 (-1.236)
INF			0.0060 (0.910)
SHARE			0.0028 (1.033)
LEV			0.0078*** (3.939)
Constant	5.8700*** (6.441)	6.8791*** (6.288)	5.9671*** (6.080)
ID	YES	YES	YES
YEAR	YES	YES	YES
N	588	588	588
R^2	0.520	0.522	0.551

Note: *,**,*** indicate 10%, 5%, and 1% significance levels, respectively.

Comparing the results of the benchmark regression (1) and regression (3), it can be found that the regression coefficient of digitalization transformation (DIG) remains unchanged at 0.0006, and the significance remains unchanged, both of which are significant at the 1% level. The goodness of fit of regression (3) is 0.551, indicating that the sample regression model is representative; the regression coefficient of digital transformation (DIG) is 0.0006, indicating that for every unit increase in the degree of digital transformation, the level of total factor productivity will be increased by 0.0006 units, and that digital transformation has a significant contribution to total factor productivity, and hypothesis 1 is valid.

5.2.2 Robustness check

In order to further test the reliability of the model and ensure the robustness of the research results. In this paper, the robustness of baseline regression was tested by replacing explanatory variables, adding control variables and proposing municipal samples respectively. The results are shown in Table 7.

In this paper, we further measure digital transformation (DIG-D) using equal weights method and then run regressions to test the robustness of the findings. The base regression results are shown in column (1) of Table 7. The results show that the regression coefficient of digital transformation (DIG) is positive and significant at 1% level, which proves that there is a significant positive correlation between digital transformation (DIG-D) on total factor productivity, which is consistent with the regression results when digital transformation (DIG) is selected as the explanatory variable.

Adding the cash flow ratio (CASHFLOW) to the control variables, the regression coefficients of digital transformation (DIG) are still significantly positive and significant at the 1% level, as shown in the results of column (2) in Table 7.

Compared to non-municipalities, municipalities are generally more efficient in terms of policy implementation and administration and have a high level and speed of economic development. These advantages make municipalities not only enjoy higher efficiency and more favorable policies, but also attract a large number of investors by providing perfect supporting facilities; the good development prospect of municipalities also attracts a large number of talents to gather and provide enterprises with high-end talents needed for their development. Both capital and talents are essential for the development of automobile manufacturing enterprises. Therefore, compared with non-municipal automobile manufacturing enterprises, the impact of digital transformation on the total factor productivity of municipal automobile manufacturing enterprises may be affected by other factors. In order to avoid the impact of these factors, the automobile manufacturing enterprises listed in the sample of municipal automobile manufacturing enterprises are excluded in this paper for regression, and the regression results are shown in Table 7, column (3) shows that the regression coefficients of digital transformation is still significant at the level of 1% level of significance.

Table 7: Robustness test results

	(1) TFP	(2) TFP	(3) TFP
DIG		0.0006*** (2.828)	0.0006*** (2.745)
DIG-D	0.0007*** (2.820)		
Controls	YES	YES	YES
Constant	5.9726*** (6.079)	6.1541*** (5.633)	5.5202*** (4.544)
ID	YES	YES	YES
YEAR	YES	YES	YES
N	588	588	504
R^2	0.551	0.552	0.563

Note: *,**,*** indicate 10%, 5%, and 1% significance levels, respectively.

5.2.3 Endogeneity test

There may be an endogeneity problem due to mutual causation in the study of this paper, digital transformation can improve the total factor productivity level of China's automobile manufacturing enterprises, but the higher the total factor productivity the more inclined and capable enterprises are to carry out digital transformation. In other words, the increase in total factor productivity level may be the cause rather than the effect of digital transformation. Therefore, this paper chooses the instrumental variable approach to address endogeneity.

This part draws on the study of Sun Chuanwang et al. (2019) and takes the lag one period of the core explanatory variable digital transformation as an instrumental variable. The digital economy is associated with its lagged one period, which satisfies the correlation. In terms of exogeneity, from the perspective of the current period, the lagged period variable is a predetermined variable that has already occurred, so the total factor productivity level in the current period will not have an impact on the digital economy in the previous period, satisfying exogeneity. The results, as shown in Table 8, show that IV is significantly and positively related to digital transformation, and the Kleibergen-Paap rk LM statistic and the Cragg-Donald Wald F statistic pass the statistical test, rejecting the instrumental variable unidentifiable and weak instrumental variable hypotheses. The second stage results show that at the 5% level, the regression coefficient (DIG) of digital transformation is significantly positive, that is, the conclusion that digital transformation has a positive impact on total factor productivity still holds.

Table 8: Endogeneity test

	(1) First	**(2) Second**
Variables	DIG	TFP
IV	0.9974*** (20.725)	
DIG		0.0013** (2.379)
Controls	YES	YES
ID	YES	YES
YEAR	YES	YES
N	539	539
R^2	0.771	0.771
Kleibergen-Paap rk LM statistic		8.734
		[0.0031]
Cragg-Donald Wald F statistic		2554.713
		{16.38}

Note: *,**,*** indicate 10%, 5%, and 1% significance levels, respectively.
The z-values are in (), the p-values are in [], and the values in {} are the critical values at the 10% significance level for the Stock-Yogo weak instrumental variable.

5.3 Mechanism test results and analysis

The results of the benchmark regression model show that digital transformation has a significant effect on the total factor productivity level of China's A-share listed automobile manufacturing enterprises, next, this paper establishes a mechanism test model to further study the issue of how digital transformation affects total factor productivity.

The results of the mechanism test based on innovation capacity are shown in column (2) of Table 9, and the results of the mechanism test based on the level of financing constraints are shown in column (3) of Table 9.

Table 9: The mechanism test results of Innovation capability (INN)

	(1) TFP	**(2) INN**	**(3) SA**
DIG	0.0006*** (2.870)	0.0167*** (2.685)	0.0005*** (6.213)
Controls	YES	YES	YES
Constant	5.9671*** (6.080)	-19.4831 (-0.901)	-3.7759*** (-9.179)
ID	YES	YES	YES
YEAR	YES	YES	YES
N	588	588	588
R^2	0.551	0.279	0.889

Note: *,**,*** indicate 10%, 5%, and 1% significance levels, respectively.

Column (1) in Table 9 is the baseline regression result of digital transformation on total factor productivity, indicating that digital transformation has a significant effect on total factor productivity. Column (2) listed as the regression results with innovation capability as the explained variable and digital transformation as the explained variable, the regression coefficient (DIG) of digital transformation is 0.0167, which is significant at 1% level, proving that digital transformation is conducive to the improvement of innovation capability. Every 1 unit increase in the degree of digital transformation, the innovation capability will be increased by 0.0167 units. Combined with the previous mechanism analysis, the innovation capacity of automobile manufacturing enterprises has a positive effect on the improvement of total factor productivity. Therefore, innovation capacity can be used as a mechanism path for digital transformation to affect the total factor productivity improvement of China's automobile manufacturing enterprises, proving that hypothesis 2 is valid.

Column (3) in Table 9 is the regression result with financing constraints as the explanatory variable and digital transformation as the explained variable, the regression coefficient of digital transformation (DIG) is 0.0005 and significant at 1% level, which proves that digital transformation reduces financing constraints, and the level of financing constraints decreases by 0.0005 units for each unit increase in the degree of digital transformation. Combined with the previous mechanism analysis, financing constraints of automobile manufacturing enterprises have a positive effect on total factor productivity. Therefore, reducing financing constraints can be used as a mechanism path for digital transformation to affect the total factor productivity improvement of China's automobile manufacturing enterprises, proving that hypothesis 3 is valid.

5.4 Moderating effect analysis

In this paper, hierarchical regression analysis is used to test its moderating effect. The first step is to regression the dependent variable to the independent variable and the regulating variable, and determine the coefficient and R^2 of each variable; In the second step, the dependent variable is returned to the independent variable, the regulating variable and the interaction term after the decentralization of the independent variable and the regulating variable, and the coefficient of each variable sum is determined. The third step is to compare the regression coefficient. If the regression coefficient of the interaction term is significant or significantly higher, the variable has a moderating effect.

The results of the moderating effect test based on debt servicing capacity (DP) are shown in Table 10.

Table 10: The results of the adjustment effect test of solvency

	(1) TFP	(2) TFP
c_DIG	0.0006*** (2.867)	0.0011*** (3.610)
c_DP1	0.0105 (0.330)	0.0851* (1.981)
c_DIG*c_DP1		0.0014*** (2.688)
Controls	YES	YES
Constant	5.9912*** (6.080)	5.9630*** (6.322)
ID	YES	YES
YEAR	YES	YES
N	588	588
R^2	0.551	0.560

Note: *,**,*** indicate 10%, 5%, and 1% significance levels, respectively.

As shown in the table above, the regression result of (1) shows 0.551, (2) adds the interaction term after digital transformation and solvency decentralization on the basis of (1), which shows 0.560, which is significantly higher than that of (1), and the regression coefficient of the interaction term is significant at the level of 1%, which proves that the moderating effect of solvency is significant.

Specifically, the coefficient of the interaction term in (2) is 0.0014, and the coefficient of digital transformation decentralization in (1) and (2) is significantly positive, and the regression coefficient increases from 0.0006 to 0.0011 after adding the interaction term.Therefore, it can be shown that stronger solvency enhances the promotion effect of digital transformation on total factor productivity, and Hypothesis 4 holds.

5.5 Threshold effect analysis

As shown in Tables 11 and 12, the non-parametric percentile Bootstrap method was applied to the threshold effect for 300, 500, and 1,000 repetitive samples to determine the presence of threshold values. Taking the results of 1000 times sampling, when operating margin (OM) is used as a threshold variable, it passes the single-threshold test at the 11% level, and the double-threshold and triple-threshold effects are not significant. Therefore, the nonlinear models of operating margin are all set to single threshold. Note that when operating margin is used as a threshold variable, the threshold estimate is 11.4003, and the lower and upper thresholds are 10.4577 and 11.7144, respectively, and the corresponding LR trend graph is shown in Figure 1.

Table 11: Threshold effect identification results

Threshold variables	Number of BS	Number of thresholds	Prob	Crit10	Crit5	Crit1
OM	300	Single threshold	0.0100	15.1618	19.6047	25.6717
		Double threshold	0.1433	14.1784	16.6427	24.0309
		Triple threshold	0.6500	17.7528	21.3722	28.6186
	500	Single threshold	0.0040	14.3783	17.5227	22.0822
		Double threshold	0.1240	13.4178	16.7531	26.2099
		Triple threshold	0.6640	17.2166	20.7120	29.7952
	1000	Single threshold	0.0060	15.3562	18.0865	25.4739
		Double threshold	0.1100	12.9190	16.7529	24.2745
		Triple threshold	0.6740	17.6739	21.5448	32.4820

Table 12: Threshold estimates and confidence intervals for threshold variables

Threshold variables	Model	Estimated threshold	95% confidence interval
OM	Single Threshold Model	11.4003	[10.4577 ,11.7144]

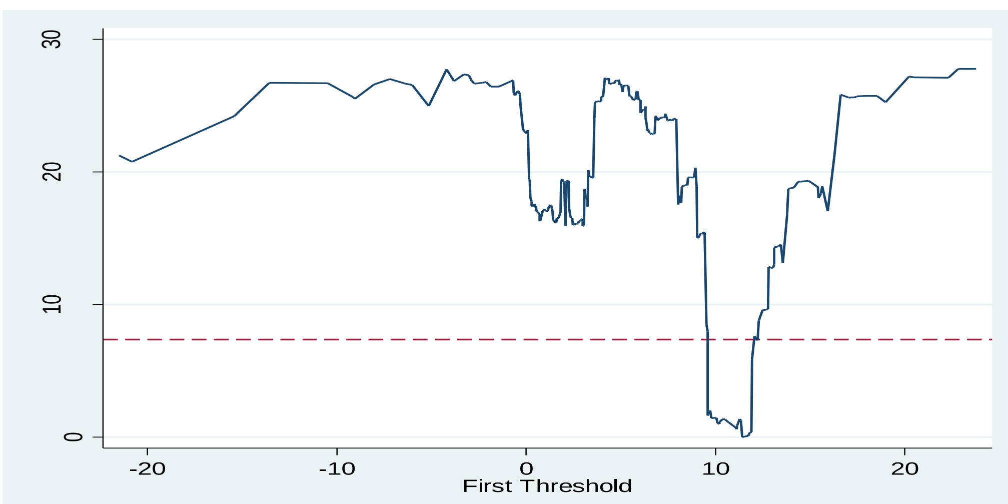

Figure 1: LR trend chart of OM

The results of the panel regression based on model (5) after estimating the threshold effects of the two variables of operating margin are shown in Table 13. Table 13 reports the results of the threshold regression for operating profit margin. In the full range of values of enterprise management efficiency, digital transformation all show significant positive impact on total factor productivity of automobile manufacturing enterprises, but when operating profit margin is smaller than the threshold value of 11.4003, the regression coefficient is 0.0007 and significant at 1% level; when crossing the threshold value, the regression coefficient rises to 0.0040 and the level of significance is still 1%. The reason for this may be that when the operating profit margin is low, the enterprise's ability to obtain profits through production and operation is weak, and the inputs are more but bring less outputs, which inhibits the enhancement of total factor productivity; however, when the operating profit margin reaches a certain value and the value is higher, it indicates that the enterprise may have achieved a certain degree of improvement in operation and management, increased sales revenue, effectively controlled costs, thus improving the profitability of the enterprise, enhancing the information of consumers, laying the foundation for the development of the enterprise, and further improving the total factor productivity of the enterprise. The automobile manufacturing industry has capital-intensive characteristics, and it is difficult to quickly recover the large amount of investment in the early stages of development, so compared to other industries, the difference in operating profit margins on the impact of all aspects of the enterprise is more pronounced, which in turn has a greater impact on the total factor productivity of the difference. In summary, the promotion effect of digital transformation on total factor productivity presents a non-linear characteristic, and hypothesis 5 is established.

Table 13: The threshold regression results of registered capital level and operating profit rate

Variables	**(1) OM**
Estimated threshold (q)	11.4003
$\mathrm{DIG} \cdot \mathrm{I}\ (\mathrm{MID} \leq q)$	0.0007*** (2.990)
$\mathrm{DIG} \cdot \mathrm{I}\ (\mathrm{MID} > q)$	0.0040*** (6.120)
Controls	YES
Number of periods	12
Number of enterprises	49
R^2	0.528

Note: *,**,*** indicate 10%, 5%, and 1% significance levels, respectively.

5.6 Heterogeneity analysis

5.6.1 Heterogeneity analysis based on urban agglomerations

There are some differences in the level of digital economy development in different regions. 2023 China Digital Economy Development Index Report shows that the level of China's digital economy development in different regions shows a ladder development pattern. And the Yangtze River Delta, Pearl River Delta, Beijing-Tianjin-Hebei, and Chengdu-Chongqing are among the top four in the overall index ranking of regional integration and high-quality development in 2022. In order to analyze this difference, it is necessary to explore the impact of this difference on total factor productivity whether enterprises are located in the four major urban agglomerations of YRD, PRD, Beijing-Tianjin-Hebei and Chengdu-Chongqing. In this paper, benchmark regressions are conducted for the two groups of samples separately, and the results are shown in columns (1) and (2) of Table 14 below.

As can be seen from the results, the regression coefficient of digital transformation (DIG) of automobile manufacturing enterprises in the four major urban agglomerations of Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, and Chengdu-Chongqing in column (1) is 0.0006, and it is significant at the 1% level, indicating that the digital transformation of automobile manufacturing enterprises in the four major urban agglomerations has a significant and positive impact on the enhancement of their level of total factor productivity; and the digital transformation of automobile manufacturing enterprises in the other regions in column (2) does not pass the significant regression coefficient of digital transformation (DIG). manufacturing enterprises do not pass the significance test, i.e., the digital transformation of automobile manufacturing enterprises outside the four major urban agglomerations does not have a significant effect on their total factor productivity level.

The possible reasons for this are that enterprises in the four major city clusters usually have stronger agglomeration economic effects and more complete infrastructure, so the promotion effect of digital transformation on total factor productivity may be more significant; and the four major city clusters have a large number of high-level universities and research institutes, which lays a foundation for the cultivation of digital talents; moreover, the four major city clusters have certain advantages in terms of policies, which makes enterprises within the clusters have a good opportunity to carry out digital transformation; the four major city clusters have a good opportunity for enterprises to carry out digital transformation. In addition, the four city clusters also have certain advantages in terms of policy, which makes the enterprises in the city clusters have a good foundation for digital transformation. On the other hand, cities that are not in the big city clusters have a weaker level of economic development and a weaker foundation for enterprises to carry out digital transformation. This result shows the importance of industrial clusters and the existence of the digital divide.

5.6.2 Heterogeneity analysis based on whether new energy vehicle enterprises

There are some differences in the degree of digital transformation of enterprises with different business scope. In October 2010, the State Council's Decision on Cultivating and Developing Strategic Emerging Industries listed new energy vehicles as a strategic emerging industry. More and more automobile manufacturing enterprises develop new energy vehicle-related businesses, which also affects their digital transformation process and total factor productivity level. In order to analyze this difference, it is necessary to explore the impact of whether enterprises develop new energy vehicle-related business on total factor productivity. The results are shown in columns (3) and (4) of Table 14 below.

Analyzing the regression results in Tables 6-18, it can be seen that the regression coefficient of digital transformation (DIG) for new energy automobile enterprises in column (3) is 0.0007 and significant at the 1% level, indicating that the digital transformation of new energy automobile enterprises has a more significant positive effect on the improvement of their total factor productivity level; the regression coefficient of digital transformation (DIG) for non-new energy automobile enterprises in column (4) is 0.0003, but it is not significant, i.e. the digital transformation carried out by new energy automobile enterprises has a stronger and more significant effect on the promotion of total factor productivity.

This may be due to the fact that, on the one hand, compared with non-energy vehicles, the higher demand of the market and consumers has forced new energy automobile enterprises to deepen the development of digital transformation, which requires a lot of technological innovation and business model innovation; and at present, new energy automobile enterprises have not yet broken through the bottlenecks in key technologies such as batteries for digital transformation, and the range and safety are yet to be improved, which requires more in-depth digitalization transformation. Whether or not to carry out digital transformation has a greater impact on new energy automobile enterprises in all aspects; on the other hand, new energy automobile enterprises have a more complete operation and management system, which is conducive to matching the depth of digital transformation with management and other institutional mechanisms, and will further expand the positive effect of digital transformation on total factor productivity.

Table 14: Heterogeneity regression results

	(1) TFP	**(2) TFP**	**(3) TFP**	**(4) TFP**
DIG	0.0006*** (3.388)	-0.0001 (-0.499)	0.0007*** (3.499)	0.0003 (0.499)
Controls	YES	YES	YES	YES
Constant	7.4542*** (5.090)	4.5866** (2.462)	4.8400*** (4.433)	5.7881*** (4.135)
ID	YES	YES	YES	YES
YEAR	YES	YES	YES	YES
N	324	264	168	420
R^2	0.636	0.525	0.728	0.506

6. Conclusions and Insights

This paper selects A-share listed automobile manufacturing enterprises from 2012 to 2023 as the research sample, involving a total of 49 enterprises. It empirically analyzes the research on the impact of digital transformation of Chinese automobile manufacturing enterprises on their total factor productivity, and then considers the mechanism effect, moderating effect, threshold effect and heterogeneity, and draws the following conclusions:

First, digital transformation has a significant positive effect on the total factor productivity of Chinese automobile manufacturing enterprises. Second, the results of the mechanism test show that both improving innovation ability and reducing the level of financing constraints faced by enterprises can be used as the mechanism path for digital transformation to affect the total factor productivity of China's automobile manufacturing enterprises. Third, according to the results of the moderating effect analysis, stronger corporate solvency plays a positive moderating role in the impact of digital transformation on total factor productivity. Fourth, the results of the threshold effect test show that operating profit margin is a threshold variable in the process of digital transformation affecting total factor productivity, and the impact of digital transformation on the total factor productivity of automobile manufacturing enterprises presents a nonlinear characteristic. Fifth, the results of the heterogeneity analysis indicate that digital transformation significantly improves the total factor productivity of firms located in the four major urban agglomerations, and new energy automobile firms. Based on the above conclusions, the paper makes the following policy recommendations.

First of all, the government should increase policy support for enterprises to carry out digital transformation. Digital transformation has become an important engine for automobile manufacturing enterprises to provide total factor productivity. The government should increase its efforts to build the infrastructure for the digital transformation of automotive enterprises; provide financial support and policy protection for enterprises to carry out digital transformation, reduce the lending rate and financing constraints of digital transformation enterprises; enhance the guidance for the digital transformation of enterprises, the government provides targeted professional guidance; create a good environment for enterprises to carry out digital transformation, strengthen the regulation of data elements and other related aspects.

Secondly, to enhance the overall level of the industry while promoting the coordinated development of the digital economy among clusters and regions to avoid the digital divide. On the one hand, the government should encourage the construction of industrial clusters, which can not only improve the overall level of China's automobile manufacturing industry, but also better utilize its external economic effect, knowledge spillover effect. On the other hand, differences in development between regions should not be ignored. The government should strengthen inter-regional policy coordination and resource allocation, and increase investment in cities outside major city clusters and industrial clusters and in enterprises within cities. Encourage enterprises in developed regions to establish cooperation mechanisms with less developed regions to enhance the latter's level of digital economy development.

Thirdly, it is important to enhance the capacity for scientific and technological innovation. In the process of promoting digital transformation to enhance total factor productivity, it is crucial to enhance scientific and technological innovation capacity. The government should increase the cultivation of scientific and technological talents, improve the talent training system, improve the quality of higher education, cultivate more high-quality talents with innovative ability and practical experience, and formulate preferential policies to attract talents. At the same time, the automobile manufacturing enterprises should also pay attention to technological innovation and the cultivation and introduction of talents.

Fourth, automobile manufacturing enterprises should enhance the awareness of digital transformation and improve the ability of digital transformation. Automotive manufacturers should not only enhance the sense of urgency of digital transformation, but also deeply realize that the long-term returns brought by digital transformation will have a positive impact on the development of enterprises in multiple aspects. In addition, many enterprises have limited ability to carry out digital transformation: the leadership's ability to formulate top-level strategies is insufficient; there are strong barriers between departments, resulting in the failure of each department to better execute the enterprise's overall digital transformation strategy, which affects the realization of the effects of digital transformation. This requires that the leadership should have comprehensive digital expertise and operational knowledge, realize that digital transformation is not only the application and innovation of technology, but also a continuous change that fully integrates with R&D, production, sales and other aspects of the enterprise, formulate a more complete and reasonable top-level strategy for digital transformation in a comprehensive manner, enhance the degree of match between the digital transformation strategy and the overall development strategy of the enterprise, so that digital transformation can have a significant impact on the total factor productivity of the enterprise. At the same time, attention should also be paid to improving operational capabilities, breaking down the barriers of different departments, establishing a unified digital transformation system, creating a data sharing platform, enhancing resource integration and sharing capabilities, improving resource allocation efficiency, enabling real-time sharing of data and plans across departments.

References

[1] Turcan, R.V. and Juho, A. (2014). What happens to international new ventures beyond start-up: An exploratory study. Journal of International Entrepreneurship, 12, pp. 129-145.

[2] Moulton, B.R. (2000). GDP and the digital economy: Keeping up with the changes. Understanding the Digital Economy: Data, Tools, and Research, pp. 34-48.

[3] Tapscott, D. (1995). Digital Economy, The Promise and Peril in the Age of Networked Intelligence. Language, 18(342), pp. 23

[4] Mesenbourg, T.L. (2001). Measuring the digital economy. US Bureau of the Census, 1,pp. 1-19.

[5] Quah, D. (2003). Digital goods and the new economy [J]. Available at SSRN , pp. 410604.

[6] Chen, X.H., Li, Y.Y., Song, L.J. et al. (2022). Theoretical System and Research Outlook of Digital Economy[J].Managing the World, 2022, 38 (02) : 208-224+ 13-16.

[7] Legner, C., Eymann, T., Hess, T., et al. (2017). Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community. Business & Information Systems Engineering, 59(04), pp. 301-308.

[8] Vial, G. (2019). Understanding digital transformation: A review and a research agenda. Journal of Strategic Information Systems, 28(2), pp.118-144.

[9] Han, J.P. and Li, Y. (2022). Digital transformation of enterprises in China: characterization, development pattern and research framework. Business and Economic Research, (06), pp. 133-135.

[10] Zhao, C.Y., Wang, W.C. and Li X.S. (2021). How Digital Transformation Affects Enterprise Total Factor Productivity. Finance, Trade and Economics, 42(07), pp. 114-129.

[11] Wu, F., Hu, H.Z., Lin, H.Y. et al. (2021). Corporate Digital Transformation and Capital Market Performance - Empirical Evidence from Stock Liquidity. Managing the World, 37(07), pp. 130-144.

[12] Huang, B., Li, H.T., Liu, J.Q. et al. (2023). Digital technology innovation and high-quality development of Chinese firms - Evidence from firms' digital patents. Economic Research, 58(03), pp. 97-115.

[13] Luo, J., Zhang, J.J. and Li, K. (2023). How Digital Technology Innovation Drives Total Factor Productivity of Manufacturing Firms? --Evidence from patent data of listed companies. Financial Research, 49(02), pp. 95-109+124.

[14] Aigner, D., Lovell, C. K. and Schmidt, P. (1976). Formulation and estimation of stochastic frontier production function models. Journal of Econometrics, 6(1), pp. 21-37.

[15] Fare, R., Färe, R., Fèare, R., et al. (1994). Production frontiers. Cambridge University Press.

[16] Syverson, C. (2011). What determines productivity? Journal of Economic literature, 49(2), pp. 326-65.

[17] Banker, R.D., Charnes, A. and Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30(9), pp. 1078-1092.
[18] Jorgenson, D.W. and Griliches, Z. (1967). The explanation of productivity change. The Review of Economic Studies, 34(3), pp. 249-283.
[19] Lu, X.D. and Lian Y.J. (2012). Estimation of Total Factor Productivity of Industrial Enterprises in China:1999-2007. Economics (quarterly), 11(02), pp. 541- 558.
[20] Blundell, R. and S. Bond. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. Tournal of Econometrics,(870), pp. 115-143.
[21] Guo, J.H., Guo M.N. and Guo S.F. (2021). How does digital infrastructure development affect firms' total factor productivity? --A quasi-natural experiment based on the “Broadband China” strategy. Securities Market Herald, (6), pp. 13-23.
[22] Guo, F., Yang, S.G. and Jin, H. (2022). The impact of digital economy on total factor productivity of enterprises and its mechanism of action. Modern Finance and Economics: Journal of Tianjin University of Finance and Economics, 42(9), pp. 20-36.
[23] Liu, F. (2020). How Digital Transformation Enhances Manufacturing Productivity - A Triple Impact Mechanism Based on Digital Transformation. Financial Sciences, (10), pp. 93-107.
[24] Wen, H., Wen, C., and Lee, C.C. (2022). Impact of digitalization and environmental regulation on total factor productivity. Information Economics and Policy, (61), pp. 101007.
[25] Ren, Y., Zhang, X. and Chen, H. (2022). The impact of new energy enterprises’ digital transformation on their total factor productivity: Empirical evidence from China. Sustainability, 14(21), pp. 13928.
[26] Bai, W.P., Sun, R.M. and Bai, G. (2022). Has the development of digital economy increased the total factor productivity of enterprises? --Analysis based on A-share listed companies. Economic and Management Review, 38(5), pp. 5-19.
[27] Tello, M. D. (2015). Firms' innovation, public financial support, and total factor productivity: The case of manufactures in Peru. Review of Development Economics, 19(2), pp. 358-374.
[28] Wu, L.C., Chen, W.H. and Lin, L. et al. (2021). Research on the impact of innovation and green technology innovation on enterprise total factor productivity. Mathematical Statistics and Management, 40(2), pp. 319-333.
[29] Wang, B. and Yan P.F. (2007). Technical Efficiency, Technological Progress and Economic Growth in East Asia - An Empirical Analysis Based on APEC Perspective. Economic Research, (05), pp. 91-103.
[30] Hong, H., Chen, X.F. and Hu, H.X. et al. (2021). Industrial Policy and Firms' Cost Stickiness - Based on Resource Allocation Perspective. Accounting Research, (1), pp. 112-131.

[31] He, F. and Liu, H.X. (2019). Assessment of the performance improvement effect of digitalization change in physical enterprises under the perspective of digital economy[J]. Reforming, (4), pp. 137-148.
[32] Li, W.J. and Zheng, M.N. (2016). Substantive or Strategic Innovation? -The Impact of Macro-Industrial Policies on Micro-Firm Innovation. Economic Research, 51(04), pp. 60-73.
[33] Hu, G.L., Zhao, Y. and Hu, J. (2019). D&O Insurance, Risk Tolerance and Firms' Autonomous Innovation. Management World, 35(08), pp. 121-135.