



The Effect of Digital Wave on Industrial Enterprises in China

Qianfan Shi

¹University of Wisconsin Madison, Wisconsin, United States of America

Email: qshi47@gmail.com

Abstract: By exploring how the digital economy impacts industrial enterprises in China, not least how it drives R&D investment in manufacturing and associated mechanisms, this paper reveals that it promotes corporate innovation significantly through enhanced technological diffusion and improved financing accessibility. Additionally, regional disparity analysis illustrates its varying impacts in central and eastern areas. A comparison of pre- and post-pandemic periods further demonstrates its growing prominence in driving R&D. Finally, policy recommendations are presented for furthering the digital economy, including fostering deeper integration of digital technologies with traditional industries, optimizing allocation of digital resources, and encouraging coordinated regional economic development.

Keywords: Digital Economy, Industrial Enterprises, R&D Investment, Technological Diffusion, Financing Accessibility, Regional Disparity, Manufacturing Upgrade

Introduction

Amidst the ongoing global economic transformation, the digital economy is emerging as a pivotal driver of economic growth and industrial evolution. As a new production factor, digitalization exerts profound influences on societal, economic, and environmental systems (Li et al., 2021a, b; Wang et al., 2021). The proliferation of advanced digital technologies—such as the Internet, information technology, the Internet of Things, cloud computing, 5G, and big data—has positioned the digital economy as a key force in facilitating industrial upgrading and fostering high-quality economic development.

The generation and exchange of industrial data are central to the digital economy (Wiebe, 2017), which is reshaping organizational structures and economic models, thereby enhancing productivity (Streltsov et al., 2019). In China, national digital policies underscore the strategic role of industrial objectives in driving digital transformation (Foster & Azmeh, 2019), which has been shown to improve production efficiency across various sectors (Kasimova et al., 2021). Moreover, the integration of digital technologies into business processes has amplified natural resource rents (Ha et al., 2022) while transforming human resource management to improve workplaces, streamline processes, and enhance economic competitiveness (Baituova et al., 2023).

In manufacturing, digital transformation enhances operational efficiency and facilitates export-import activities (Pyroh et al., 2021; Li et al., 2022). At a regional level, the digital economy plays a significant role in upgrading provincial industrial structures (Su et al., 2021) and aligns closely with the principles of the circular economy through digital sharing platforms (Schwanholz & Leipold, 2020). Furthermore, it boosts technological innovation and promotes green economic efficiency (Chen et al., 2021; Li et al., 2021a, b).

The digital economy also influences entrepreneurship and economic agglomeration by enhancing output and employment density (He et al., 2022; Jiang et al., 2022). It supports urban low-carbon sustainable development through the mobility of innovation factors (Dou & Gao, 2022; Wang et al., 2021) and drives green total factor productivity by improving technological efficiency and reducing technology gaps (Han et al., 2022; Hu & Guo, 2022; Meng & Zhao, 2022). Finally, the rapid growth of the digital economy significantly mitigates haze pollution in various urban contexts, including resource-based and non-resource-based cities, as well as large metropolitan areas (Che & Wang, 2022).

This multifaceted impact underscores the transformative potential of the digital economy in advancing sustainable and innovative economic systems.

Literature Review

The Impact of the Digital Economy on R&D Investment in Manufacturing Enterprises

The digital economy has significantly stimulated innovation, research, and investment in new products, technologies, and projects. On the one hand, it provides firms with advanced tools and platforms, thereby enhancing their technological innovation capacity. For example, through data mining, firms can better understand market demands and develop products that are more aligned with consumer preferences. Against the backdrop of growing attention to the digital economy, the ratio of R&D expenditure to operating revenue has increased, resulting in heightened innovation output. As firms increasingly prioritize the digital economy, their R&D expenditure ratios also rise. This is consistent with the findings of Chen, Gu, and Luo (2022) and Griliches (1981), which demonstrate a significant and robust relationship between corporate R&D expenditure and patent applications. These results suggest that heightened focus on the digital economy



not only increases R&D expenditure but also leads to greater innovative outcomes, reinforcing the role of the R&D expenditure mechanism.

On the other hand, the digital economy reduces sales costs and alleviates financial pressure on R&D investments by fostering the growth of online sales channels. The digital economy has catalyzed the expansion of e-commerce, enabling firms to achieve cost savings in sales processes, which in turn facilitates innovation activities. Empirical evidence indicates that the degree of engagement with the digital economy is negatively associated with sales expenses. This reflects the ability of digital transformation to lower sales costs, primarily due to the efficiency gains offered by online sales. By broadening online sales channels, the digital economy not only reduces corporate sales expenditures but also lowers consumers' market search costs. Consequently, firms can promote new products more effectively at a reduced cost. Moreover, innovation activities can more precisely track market demand trends and match customer needs on a broader scale. The reduction in sales expenses can further alleviate financial constraints on R&D investment, indirectly exerting a substantial and positive impact on the generation of invention patents (Wu Qinqin et al., 2023).

The Mediating Effect of Technology Diffusion Degree

First of all, the development of the digital economy enhances the diffusion capacity of technological innovation, particularly exerting a greater impact on inventions with higher technological content. The digital economy significantly boosts the diffusion capacity of technological innovations through accelerated information flow, construction of innovation networks, and optimization of dissemination pathways. It effectively transcends geographical boundaries by leveraging digital technologies such as the internet and big data to strengthen interregional connections and interactions. These connections facilitate the sharing of innovative knowledge and resources, fostering an overall enhancement in the technological innovation capabilities across regions. This not only accelerates the rapid release of technological dividends but also provides crucial impetus for regional economic growth and social progress. In the future, with ongoing breakthroughs in digital technologies and the continuous improvement of the digital economy ecosystem, its role in the diffusion of technological innovation will become even more pronounced (Wen Jun et al., 2019).

Secondly, the diffusion capability of technological innovation can enhance corporate innovation investment. The advancement in research and development brought about by scientific research and technological innovation is one of the key factors for improving a company's competitiveness and supporting its development. Innovation is crucial to the sustainable development and competitiveness of enterprises. In an increasingly competitive market environment, companies must engage in continuous technological innovation to survive and grow. Technological innovation is a significant aspect of achieving globalization and economic growth for enterprises. Through technological innovation, production costs can be reduced, production functions enhanced, and product competitiveness strengthened (Yuhan Hu et al, 2019).

The enhancement of technological innovation diffusion capabilities can effectively promote corporate innovation investment. As the speed and scope of technology dissemination expand, corporate costs in acquiring, assimilating, and applying cutting-edge technologies decrease significantly, creating more favorable conditions for corporate innovation investment. The improvement in technology diffusion capabilities allows companies to leverage the research outcomes of others in their R&D processes, thereby reducing the need for repetitive resource inputs and significantly shortening the innovation cycle. For instance, through technology cooperation networks and industry standardization platforms, companies can quickly identify suitable technological solutions, enabling them to launch new products or optimize production processes more rapidly. This accelerated innovation effect increases the expected returns on investment, further encouraging companies to enhance their innovation input. The improved diffusion capability of technological innovation provides a superior external environment for corporate innovation investment. In this process, the reduction in technology acquisition costs, shortened R&D cycles, and enhanced innovation collaboration create higher investment return expectations and stronger competitive incentives for companies. In the future, as the diffusion capability of technology continues to strengthen, corporate innovation investment levels are expected to keep rising, injecting robust momentum into high-quality economic development (Guisheng Wu, 2000).

Lastly, the facilitative effects of the digital economy on technological innovation capacity exhibit variability across different regions. In economically underdeveloped western regions, the digital economy's impetus is more significant, whereas its impact is relatively smaller in eastern regions that already possess a high level of technological innovation. Thus, different regions need to formulate targeted strategies for digital economy development. Additionally, in the short term, the advancement of the digital economy markedly enhances regional technological innovation capacity and generates positive spatial spillover effects on neighboring regions. For example, the improvement of one region's digital economy development level can exert a radiating influence on the technological innovation capacities of surrounding areas (Tian, 2023).

The Mediating Effect of Financing Accessibility

On one hand, the digital economy can enhance financing accessibility. The development of the digital economy has significantly improved the convenience of financing, offering businesses and individuals more financing channels, more efficient processes, and fairer opportunities for obtaining capital. The digital economy and digital finance, stemming from the internet revolution, can benefit groups previously excluded by traditional finance and credit systems. This helps alleviate their borrowing constraints and promotes their investment and business activities (Xun Zhang et al, 2019).

Through online financial platforms, digital payment systems, and blockchain technology, the digital economy creates more diversified financing avenues for businesses and individuals. For example, crowdfunding platforms, P2P lending

platforms, and supply chain finance platforms break the limitations of the traditional banking system, enabling small and medium-sized enterprises (SMEs) and entrepreneurs to access funding at lower costs. This inclusive finance model significantly reduces financing barriers, which is especially important for small and micro-enterprises that find it difficult to obtain loans within the traditional financial system.

On the other hand, ease of financing can enhance corporate innovation investment. Research findings indicate that digital finance significantly improves the innovation efficiency of enterprises, with expanding the coverage of digital finance being more crucial for enhancing enterprise innovation efficiency than intensive usage. In terms of transmission mechanisms, digital finance aids enterprises in achieving digital transformation, thereby promoting an increase in innovation efficiency. Compared to non-state-owned enterprises, digital finance has a more pronounced effect on enhancing the innovation efficiency of state-owned enterprises (Hainan Wang and Fengshuo Liu, 2024). In rapidly changing innovation markets, companies need to access funds quickly at critical moments to seize technological breakthroughs or market opportunities. With improved ease of financing, companies can secure quick loans or instant fund transfers through digital finance platforms, significantly shortening the financing cycle. For instance, some online financing tools can complete reviews and disburse funds within hours, allowing companies to swiftly launch innovative projects. This increase in efficiency helps companies gain a competitive edge.

Data, Variables and Model Specification

Data Source

The regions selected in this study include 22 provinces, 5 autonomous regions, 4 directly governed municipalities, and 2 special administrative regions in China. Specifically, these are: Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, Tibet Autonomous Region, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, Beijing, Tianjin, Shanghai, Chongqing, Hong Kong Special Administrative Region, and Macau Special Administrative Region.

This study uses the Digital Inclusive Finance Index released by the Digital Finance Research Center at Peking University to represent the development level of digital finance from 2011 to 2022. The center, in collaboration with Ant Financial Research Institute, constructed 33 specific indicators across three dimensions—breadth of digital finance coverage, depth of digital finance usage, and degree of financial inclusion—utilizing vast data from Ant Financial to measure the Digital Financial Inclusion Index. Adopting the Analytic Hierarchy Process, the "Digital Inclusive Finance Index" by Peking University is divided into three levels, covering 31 provinces, 337 cities, and 2800 counties in mainland China. Following the entropy method used by Guo Feng et al. (2020) to estimate the level of digital economy, this study evaluates the digital economy using 12 indicators (Table 1) : the number of IPv4 addresses at the provincial and city levels, number of internet access ports, mobile phone penetration rate, length of long-distance fiber-optic cables per unit area, number of information technology enterprises, number of websites per hundred enterprises, e-commerce transaction volume (in billion RMB), proportion of enterprises engaged in e-commerce activities, software business revenue (in ten thousand RMB), index of digital financial coverage breadth, index of digital financial usage depth, and degree of digitalization in finance. The number of internet access ports is based on broadband internet users per hundred people, and the relevant output is measured by total telecommunications business per capita, while the mobile phone penetration rate is based on the number of mobile phone users per hundred people in China.

After standardizing these twelve indicators, the entropy method was applied to measure the digital economy development status across the 31 provinces. Other related variables, such as the number of employees in industrial enterprises above a certain scale, investment and research funding, project numbers, internet access numbers per hundred people, annual provincial patent application numbers for larger enterprises, and records on annual foreign investment registration at the provincial level, are primarily sourced from the China Economic Statistical Database, the China Research Data Service Platform, China Economic Information Database, as well as annual editions of the "China Industrial Statistical Yearbook," "China Statistical Yearbook," and the statistical yearbooks of various provinces.

Index	Variable	Unit	Stats
Three-Level Index	Number Of Ipv4	number	positive
	Number Of Internet Access Ports	number	positive
	Mobile Phone Penetration	%	positive
	Length Of Long-Distance Cable Per Unit Area	m	positive
	Number Of Informatization Enterprises	number	positive
	Number Of Websites Per 100 Companies	number	positive
	e-Commerce Transaction Volume	100 million yuan	positive
	Proportion Of Enterprises With e-Commerce Transaction Activities	%	positive
	Software Revenues	ten thousand yuan	positive
	Digital Financial Reach Index	/	positive
	Digital Finance Usage Depth Index	/	positive
	Digital Finance Digitization Degree	/	positive

Table 1 : Indicators Description

Variable Specification

Digital Economy:

The digital economy, as one of the most critical factors of production in the current era, exerts a comprehensive and profound impact on our production, life, and ecology. This paper employs the digital economy as the core explanatory variable, referencing the measurement method of the digital economy level as discussed by Guo Feng, Wang Jingyi, Wang Fang, et al. (2020), using the entropy method for calculation. In particular, the forementioned 12 indicators originate from different levels, with significant differences in their dimensions and magnitudes. Therefore, only after normalizing these diverse indicators can they achieve horizontal comparability and practicality, ensuring the accuracy of the ultimately estimated index. The formulas for handling positive and negative indicators are as follows:

The positive indicator

$$x_{ij} = \frac{x_{ij} - \min\{x_j\}}{\max\{x_j\} - \min\{x_j\}} \quad (1)$$

The negative indicator

$$x_{ij} = \frac{\max\{x_j\} - x_{ij}}{\max\{x_j\} - \min\{x_j\}} \quad (2)$$

Where $\max\{x_j\}$ is the maximum value of the indicator in all years, $\min\{x_j\}$ is the minimum value of the indicator in all years, and x_{ij} is the result of non-dimensionalization. After normalizing the indicators, the objective weight of each indicator is calculated according to the entropy method steps used by Wang Jun et al. (2013).

Calculate the proportion of j index in year i , and use ω_{ij} to represent:

$$\omega_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$$

To calculate the information entropy e_j of the indicator, we have:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m \omega_{ij} \times \ln \omega_{ij}$$

To calculate the redundancy of information entropy d_j :

$$d_j = 1 - e_j$$

Here, m refers to the evaluation year, and the indicator weights are calculated based on the redundancy of information entropy φ_j :

$$\varphi_j = \frac{d_j}{\sum_{j=1}^m d_j}$$

Based on the standardized indicator x_{ij} and the calculated indicator weight φ_j , the level of digital economic development index (DED CI_i) is determined using a weighted multiple linear function. The formula is as follows:

$$DED\mathbf{CI}_i = \sum_{j=1}^m \varphi_j \times \omega_{ij}$$

The comprehensive index of digital economic development is calculated using the above formula, where DED CI_i represents the comprehensive digital economic development index for province i , ranging between 0 ~ 1. A larger DED CI_i indicates a higher level of digital economic development, whereas a smaller DED CI_i suggests a lower level of digital economic development.

Judging from the estimated results of the comprehensive index of digital economic development (DED CI) measured by the entropy method from 2011 to 2022, it is evident that there is significant regional heterogeneity in the level of digital

economic development. The eastern region has a large stock of digital economic development, leading to slower growth; in contrast, other regions have lower DEDCI levels, resulting in faster growth rates. However, both the western and central regions exhibit growth rates that surpass those of the eastern region. A closer examination of the regional heterogeneity in digital economic development reveals a pronounced catch-up effect in the western, central, and northeastern regions, indicating substantial potential for further development. (Wang Jun et al., 2021)

Corporate R&D and Investment

This paper uses "R&D expenditure of large-scale industrial enterprises" as the core dependent variable Y2 to evaluate the impact of the digital economy on the manufacturing sector. According to the definition by the National Bureau of Statistics of China, "large-scale industrial enterprises" refer to those industrial enterprises with an annual main business income reaching a certain threshold. Specifically, these are industrial legal entities with an annual main business income of 20 million RMB or more. This classification facilitates a more precise analysis of the economic activities of large industrial enterprises, economic monitoring, policy formulation, and assessment of economic growth levels. Additionally, these data are widely used for international comparisons to measure the scale and vitality of industrial development in a country or region. The "R&D expenditure of large-scale industrial enterprises" employed in this study is collected from the National Bureau of Statistics and encompasses the expenditures on research and development by industrial enterprises that meet the scale criteria across 31 provinces, autonomous regions, and municipalities in China, reported in units of 100 million RMB. R&D activities generally refer to systematic and creative work undertaken by enterprises to enhance their knowledge base, develop new products, and improve production processes, serving as a critical indicator of the developmental level of industrial enterprises. (Ren Haiyun and Shi Ping, 2009)

Control Variable

Variable	Symbol	Definition
Explained Variable 1	Y1	Full-time equivalent of R&D personnel in industrial enterprises above designated size
Explained Variable 2	R&D(Y2)	R&D Expenditure of Large-Scale Industrial Enterprises
Explained Variable 3	Y3	"Number of R&D projects in industrial enterprises above designated size"
Digital Economy Index	digit	Level of Digital Economy Development
Output of the Primary Industry	X2	Regional GDP Index - Primary Industry (Previous Year = 100)
Output of the Industry	X4	Regional GDP Index - Industry (Previous Year = 100)
Local Fiscal Revenue	X12	Revenue from Local State-Owned Capital Operations (Billion RMB)
Local Fiscal Asset Revenue	X13	Revenue from the Paid Use of Local State-Owned Resources (Assets) (Billion RMB)
Number of Industrial Enterprises	X15	Number of Industrial Enterprises above Designated Size (Units)
Number of Loss-Making Industrial Enterprises	X16	Number of Loss-Making Industrial Enterprises above Designated Size (Units)
Collective Capital of Industrial Enterprises	X19	Collective Capital of Industrial Enterprises above Designated Size (Billion RMB)
Paid-in Capital of Industrial Enterprises with Legal Person Status	X20	Paid-in Capital of Industrial Enterprises with Legal Person Status above Designated Size (Billion RMB)
Individual Capital of Industrial Enterprises	X21	Paid-in Capital of Industrial Enterprises above Designated Size (Billion RMB)
Capital from Hong Kong, Macao, and Taiwan in Industrial Enterprises	X22	Capital from Hong Kong, Macao, and Taiwan in Industrial Enterprises above Designated Size (Billion RMB)
Main Business Revenue of Industrial Enterprises	X27	Main Business Revenue of Industrial Enterprises above Designated Size (Billion RMB)
Financial Expenses of Industrial Enterprises	X28	Financial Expenses of Industrial Enterprises above Designated Size (Billion RMB)
Interest Expenses of Industrial Enterprises	X30	Interest Expenses of Industrial Enterprises above Designated Size (Billion RMB)
Total Profits of Industrial Enterprises	X31	Total Profits of Industrial Enterprises above Designated Size (Billion RMB)
Measure1	IV(one)	Number of Fixed-line Telephones per 100 People in 2011 * National IT Service Revenue of the Previous Year
Measure2	IV(two)	Number of Post Offices per Million People in 2011 * National IT Service Revenue of the Previous Year

Table 2: Variable Definitions

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Y2	372	383.903	525.849	.164	3217.755
digi	360	0	.703	-1.044	3.368
X2	217	103.866	2.615	86.393	108.6
X4	217	-32.68	95.544	-95	122.2
X12	349	32.635	51.649	-100.366	285.63
X13	372	201.509	193.878	2.21	1472.942
X15	372	12421.266	13988.568	56	70702
X16	217	1321.406	1387.815	14	6405
X19	217	109.359	107.678	1.29	513.532
X20	217	2194.671	1664.807	50.978	8264.95
X21	217	1396.235	1694.962	4.342	13582.479
X22	214	439.009	1029.633	1.3	10856.576
X27	248	33633.336	35142.969	72.633	156591.04
X28	248	28466.944	30297.766	56.459	134083.08
X30	372	378.219	309.921	.729	1667.65
X31	217	388.167	323.132	.983	1482.71

Table 3 : Descriptive Statistics

Table 3 reports the descriptive statistics for each variable. The average research and investment funding for industrial enterprises above a designated size nationwide is 38.3903 billion yuan, with values ranging widely from a minimum of 0.164 billion yuan to a maximum of 3217.755 billion yuan, indicating a significant disparity in the level of research funding among enterprises. The Digital Economy Index exhibits a trend of polarization, attributed to its broad distribution and certain volatility. The considerable difference between the minimum and maximum values of the Digital Economy Index (ranging from -1.044 to 3.368) suggests a large disparity in digital economy development within the sample, reflecting differences across regions and time dimensions. Although the overall data may not be biased toward either the positive or negative direction (with a mean of 0), the presence of extreme values indicates that some regions or individual samples exhibit extreme levels of digital economy development.

Theoretical Analysis and Hypothesis Design

The digital economy utilizes new-generation information technology and digital knowledge information as key production factors, with digital technologies such as mobile internet, cloud computing, and the internet of things acting as important carriers. Hao et al. (2022) found that the digital economy has promoted the development of manufacturing industries in 30 provinces in China and significantly improved the green total factor productivity of China's manufacturing sector. From the perspective of the decomposition of manufacturing green total factor productivity, the digital economy has a significant positive effect on the technological efficiency of manufacturing. Therefore, we make the following hypothesis:

Hypothesis 1:

The rapid development of the digital economy promotes research and development investment by manufacturing enterprises, fostering the development of the manufacturing sector.

After the outbreak of COVID-19, China's economic and social development was severely impacted. According to forecasts by China International Capital Corporation (CICC), with the rapid and comprehensive escalation of overseas epidemics and quarantine measures, the contraction of overseas economies in the second to third quarters of 2020 is expected to exceed the levels of 2008-2009. The global coronavirus pandemic may negatively affect China's annual GDP by 7-8 percentage points. During the response to the epidemic, the digital economy played an important role and presented certain development opportunities. After the epidemic, due to the downward pressure on the economy, the role of the digital economy in manufacturing enterprise research and development and investment has become more prominent. (Tian et al, 2020). Therefore, the second hypothesis is proposed:

Hypothesis 2:

After the outbreak of the epidemic, the impact of the digital economy on enterprise scientific research will be more significant.

Model Construction

Baseline model:

This paper employs the method for measuring the level of digital economy development in China proposed by Wang et al. (2021) to calculate digital economy indicators for 31 provinces, autonomous regions, and municipalities in China. Based on Hypothesis 1, it empirically tests the impact of the digital economy wave on China's manufacturing enterprises. The following Dual fixed effect model is used in this paper to test the impact of digital economy development on the manufacturing sector:

$$R \& D_{it} = \beta_0 + \beta_1 digi_{it} + \beta_2 X_{it} + \varphi_t + c_i + \varepsilon_{it} \quad (8)$$

Among the equation (8) intercept term β_0 ; β_1 is the coefficient of $digi_{it}$. X_{it} is control variable set matrix. φ_t is time fixed effect. c_i is fixed effects for individuals. ε_{it} is random error term. With positive coefficient and p-value less than 0.05, check whether control variable X_{it} can be added one by one. Finally, we selected 15 control variables:

$$X_{it} = [X_{2t} X_{4t} X_{12t} X_{13t} X_{15t} X_{16t} X_{19t} X_{20t} X_{21t} X_{22t} X_{27t} X_{28t} X_{30t} X_{31t}] \quad (9)$$

$t = 2011 \dots 2022$, X_{2t} to X_{31t} : described in Table 2.

Extended Model

Constructing the crossing item $digi_{it} * covid_{it}$ to determine whether there is an impact on the digital economy before and after the epidemic:

$$R \& D_{it} = \beta_0 + \beta_1 digi_{it} + \beta_2 covid_{it} + \beta_3 digi_{it} * covid_{it} + \beta_4 X_{it} + \varphi_t + c_i + \varepsilon_{it} \quad (8)$$

It is predicted that after the outbreak of the epidemic, the impact of the digital economy on enterprise scientific research will be more significant. Because after the epidemic, due to the downward pressure on the economy, the role of the digital economy in scientific research has become more prominent.

Two-part Mediation Model

Due to the strict assumptions relied upon by the three-step method, such as the exogeneity of the mediator variable, which are difficult to satisfy in practical economic research, especially in analyses based on observational data, this paper adopts the two-step method as the mediation mechanism, referencing the analysis of mediation and moderation effects in empirical research on causal inference by Jiang et al. (2022). The two-step method emphasizes the statistical significance test of indirect effects, directly testing their significance by estimating the indirect effects.

Firstly, the capability for technology innovation diffusion used by Wang Baichuan et al. (2022) is selected as the mediator variable. The digital economy influences the capability for technology innovation diffusion of industrial enterprises above a designated size, which in turn affects the R&D and investment of these enterprises, forming a complete mediation mechanism transfer chain. We adopt the method by Wang (2022) to measure the capability for technology innovation diffusion, using the number of technology patent applications to assess the capability of industrial enterprises. Therefore, provincial-level statistics on patent applications are used as the mediator. Secondly, using the method by Yang et al. (2017), financing convenience is chosen as the second mediator variable. After the enhancement of the digital economy, the financing convenience for enterprises in the region improves. With improved financing convenience, investment in innovation may increase because more financing means increased available capital for enterprises, and thus more funds for research and investment. In private enterprises, the entry of foreign banks mainly improves investment efficiency by alleviating financing constraints (Yang et al., 2017). Therefore, the degree of foreign bank entry is selected as the second mediator variable.

$$Fina_{it} = \beta_0 + \beta_1 digi_{it} + \beta_2 X_{it} + \varphi_t + c_i + \varepsilon_{it} \quad (10)$$

$$R \& D_{it} = \beta_0 + \beta_1 Fina_{it} + \beta_2 X_{it} + \varphi_t + c_i + \varepsilon_{it} \quad (11)$$

$$Tech_{it} = \beta_0 + \beta_1 digi_{it} + \beta_2 X_{it} + \varphi_t + c_i + \varepsilon_{it} \quad (12)$$

$$R \& D_{it} = \beta_0 + \beta_1 Tech_{it} + \beta_2 X_{it} + \varphi_t + c_i + \varepsilon_{it} \quad (13)$$

Among which $Fina_{it}$ represents the degree of foreign bank entry, and $Tech_{it}$ represents the number of technology patent applications.

Empirical Results

Benchmark regression

Table 4 presents the results of the benchmark regression, indicating that the level of the digital economy has a significant positive impact on firms' R&D expenditures. From columns (1) to (4), control variables and fixed effects are gradually introduced. In column (1), there is a significant positive correlation between the digital economy and R&D expenditure of large-scale industrial enterprises. For every unit increase in the digital economy, R&D expenditure increases by 48.5987 billion yuan. In columns (1) and (2), without controlling for other variables, the coefficients of the digital economy are

485.987 and 446.011, both significant at the 1% level. In columns (3) and (4), after gradually controlling for year and individual fixed effects, the significant positive impact of the digital economy on R&D investment persists, with coefficients of 79.795 and 67.274, respectively. As the coefficients decrease from column (1) to column (4) and the R-squared values increase, this suggests that the model construction is reasonable. In the dual fixed-effects model with control variables in column (4), the coefficient is 67.274. This indicates that for every unit increase in the digital economy, R&D expenditure of large-scale industrial enterprises in the region increases by 67.274 billion yuan. From columns (1) to (4), year and individual fixed effects are gradually introduced. Although the coefficient of the digital economy declines, it remains significantly positive, indicating that even when controlling for fixed effects, the positive impact of the digital economy on R&D expenditure of large-scale industrial enterprises remains significant. This supports the previous analysis that the digital economy promotes the development of corporate R&D activities and indirectly stimulates such development.

Endogeneity Analysis

In this study, we selected internet access as an instrumental variable. This choice is based on the following reasons: First, there is a significant correlation between the level of internet access and the development of the regional digital economy (the core explanatory variable in this study, digi). Higher internet access typically indicates an increase in internet users within a region, further promoting the flourishing of the digital economy. However, the relationship between internet access and corporate research and investment funding (the core dependent variable Y2 in this study) is not significant. Therefore, internet access can be considered a suitable instrumental variable.

VARIABLES	(1) Y2	(2) Y2	(3) Y2	(4) Y2
digi	485.987*** (304,751)	446.011*** (478,226)	79.795*** (159,428)	67.274*** (199,131)
X2			87.875*** (27,607)	8,944 (21,019)
X4			499.1 (490.7)	1,190 (1,820)
X12			-7,134*** (1,160)	-5,236*** (1,239)
X13			3,583*** (528.5)	3,588*** (520.5)
X15			-32.71** (15.71)	-99.75*** (23.28)
X16			1,156*** (108.2)	1,318*** (128.5)
X19			-39.72 (801.8)	931.2 (610.5)
X20			-187.5** (74.49)	254.4*** (70.83)
X21			15.98 (46.68)	64.57* (33.14)
X22			5.302 (73.51)	-61.76 (55.18)
X27			327.5*** (63.54)	458.5*** (63.18)
X28			-272.5*** (71.37)	-425.2*** (71.15)
X30			1,773 (1,223)	29.36 (1,020)
X31			-3,960*** (1,281)	-2,427** (953.1)
Constant	3.967e+06*** (213,808)	4.057e+06*** (788,452)	-9.508e+06*** (2.854e+06)	-1.700e+06 (2.142e+06)
Control Variable	-	-	Control	Control
Year Fixed Effect	No	Yes	No	Yes
Individual Fixed Effect	No	Yes	No	Yes
Observations	360	360	197	197
R-squared	0.415	0.476	0.976	0.977

Table 4: Benchmark regression

Note. Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

To construct specific instrumental variables, we utilized data from the China Statistical Yearbook over the years, extracting the number of fixed-line telephones in 2011 (measured in ten thousand households) and the number of post offices (measured per million people). Subsequently, we multiplied these 2011 figures by the previous year's national information technology service revenue to create two interaction terms, which serve as the instrumental variables for this study. The design of these instrumental variables aims to isolate the impact of internet access on the development of the digital economy while controlling for its direct relationship with corporate research and investment funding, thereby ensuring the validity of the instrumental variables and meeting identification requirements. This approach provides us with a scientifically rigorous foundation to explore the impact of the digital economy on corporate research and investment activities.

In the second stage GMM estimation, the regression coefficient is 2,783,926 and is significant at the 1% level, indicating that "digi" has a significant positive effect on Y2. The figures indicate that for each unit increase in "digi1," R&D funding for industrial enterprises above a designated size increases by 27.83926 billion yuan. The Hansen J test for over-identification has a p-value of 0.9775 (greater than 0.05), and thus, we cannot reject the null hypothesis of the exogeneity of the instrumental variables, indicating that the instrumental variables are valid. The GMM method addresses the endogeneity problem, making the results more reliable. The validity tests of the instrumental variables and the significance of the core variables jointly support the causal inference of this model. (Table 5)

Variables and statistics	First-stage regression results	Second-stage regression results
digi (Digital Economy Index)	2.20e-07*** (6.54e-08)	2,783,926*** (640,896)
X2 (Enterprise size)	-0.105*** (0.0168)	289,886*** (81,557)
X4 (Fixed asset ratio)	0.004*** (0.0009)	-6,991** (3,414)
X13(Enterprise profitability)	-0.00087*** (0.0002)	5,368*** (807)
X16 (Capital liquidity)	0.00018** (0.00007)	1,034*** (236)
Year fixed effects	Yes	Yes
Individual fixed effects	Yes	Yes
Constant term (_cons)	9.782*** (1.810)	-28,100,000*** (7,944,347)
F-value(instrument relevance)	7.44	
P-value(instrument relevance)	0.0009	

Table 5: Endogeneity Analysis

Robustness Analysis

Replace Variables

Previously, we conducted a regression analysis on the digital economy using R&D investment data from large-scale industrial enterprises. To ensure the robustness of the analysis results, we have now performed a replacement variable test. In the latest analysis, we substituted the original R&D investment data with the full-time equivalent of R&D personnel and the number of R&D projects in large-scale industrial enterprises to reanalyze the digital economy. This approach allows us to verify the reliability and robustness of the analysis results, thereby gaining a more comprehensive

understanding of the impact of R&D on the development of the digital economy. This process helps confirm that the original analysis conclusions are not affected by the choice of a few variables, thus ensuring the robustness of the conclusions (Table 6).

VARIABLES	(1) Y1	(2) Y3
digi	10,775** (5,369)	3,105** (1,285)
X2	-64.76 (621.6)	118.6 (175.3)
X4	9.450 (55.50)	-6.610 (16.32)
X12	-39.85 (34.49)	-23.84*** (8.690)
X13	3.029 (15.38)	9.908** (4.165)
X15	3.402*** (0.586)	0.641*** (0.139)
X16	24.65*** (3.370)	3.326*** (0.807)
X19	-32.06* (18.16)	4.484 (5.110)
X20	9.699*** (2.062)	2.869*** (0.553)
X21	-1.795* (0.960)	-0.384 (0.273)
X22	9.099*** (1.630)	-0.639 (0.450)
X27	0.197 (0.198)	-0.111** (0.0485)
Constant	-6,754 (63,214)	-13,987 (17,845)
Observations	197	197
Number of ID	30	30

Table 6: Replace Variables

Note: Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Comparing the new regression results with the original ones, the coefficients for the number of R&D personnel in industrial enterprises and the number of R&D projects in large-scale industrial enterprises with respect to the level of the digital economy are 10.775 and 3.105, respectively. These coefficients remain significant at the 95% significance level, indicating the model's robustness. Based on the results of the robustness check, the research hypothesis is further refined to suggest that the improvement in the level of the digital economy can promote various aspects of development in manufacturing enterprises.

Replace Regression Model

Binarize the variable $digi$ based on its mean to create a binary treatment variable 'digi_', indicating whether treatment was received or not. Specifically, if $digi$ is greater than or equal to the mean, the generated binary variable 'digi_' will have a value of 1; if 'digi' is less than the mean, then $digi$ — will have a value of 0. The result is a new binary variable $digi$ — that indicates whether the value of 'digi' is above or equal to its average level. Variables X2, X4, X12...X31 are covariates used to estimate the propensity score of $digi$ — . Based on these covariates, a model (default is logistic regression) is used to estimate the probability of each observation being in the treatment group $digi$ — = 1, which is the propensity score.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
nearest neighbor matching	Unmatched	6972015.25	1558655.24	5413360	471213.422	11.49
	ATT	6972015.25	2442854.95	4529160.29	1231869.46	3.68
caliper matching	Unmatched	6972015.25	1558655.24	5413360	471213.422	11.49
	ATT	1581229.75	2381424.58	-800194.827	570035.153	-1.40
radius matching	Unmatched	6972015.25	1558655.24	5413360	471213.422	11.49

kernel matching	ATT	1581229.75	2170227.49	-588997.736	526727.028	-1.12
	Unmatched	6972015.25	1558655.24	5413360	471213.422	11.49
	ATT	6972015.25	2255837.17	4716178.08	1209162.68	3.90

Table 7: Propensity Score Matching

Heterogeneity Analysis

According to the regression results, there is significant heterogeneity in the effects of the digital economy on the R&D and investment expenses of large-scale industrial enterprises across the eastern, central, and western regions. In the eastern region, the regression coefficient of the digital economy is 74.03 and is significant at the 1% level, indicating that the influence of digital economy growth on industrial enterprises' R&D and investment expenses is smallest. In the western region, the regression coefficient is 148.9 and significant at the 1% level, suggesting a moderate influence. The central region has the highest impact, with a coefficient of 390.8, also significant at the 1% level. This is consistent with the analysis mentioned earlier. Although spatially, China's digital economy level shows a stepped decreasing trend from east to west—with the eastern region having the highest level, followed by the central region, and the western region being the weakest—the growth rate of digital economy development in Beijing, Shandong, Jiangsu, Zhejiang, Shanghai, and Guangdong in the eastern region is relatively slow. In contrast, the growth rate in the central and western regions is rapid. (Table 8)

VARIABLES	East Y2	Middle Y2	West Y2
digi	74.03*** (22.58)	390.8*** (71.55)	148.9*** (15.69)
X2	7.985** (3.923)	-4.456 (4.871)	-3.166 (2.028)
X4	0.146 (0.328)	-1.208 (4.627)	2.609 (1.614)
X12	-0.883*** (0.173)	0.229 (0.392)	0.265*** (0.0901)
X13	0.508*** (0.0828)	0.0188 (0.126)	0.221*** (0.0527)
X15	0.00136 (0.00302)	-0.00582 (0.00370)	-0.00763*** (0.00218)
X16	0.0849*** (0.0166)	0.129*** (0.0407)	0.0343** (0.0170)
X19	0.193 (0.119)	0.141 (0.104)	0.0159 (0.0470)
X20	-0.0126 (0.0142)	0.00923 (0.0156)	-0.00383 (0.00425)
X21	0.00664 (0.00568)	-0.0241* (0.0127)	-0.00267 (0.00828)
X22	-0.00347 (0.00838)	0.0675 (0.199)	-0.159* (0.0946)
X27	0.0319** (0.0130)	0.0699*** (0.0186)	0.0130*** (0.00444)
X28	-0.0269* (0.0151)	-0.0726*** (0.0205)	-0.00879 (0.00537)
X30	-0.114 (0.178)	0.645 (0.394)	-0.277* (0.160)
X31	-0.179 (0.162)	-0.807** (0.372)	0.232 (0.179)
Constant	-911.6** (396.9)	766.9 (757.2)	130.0 (297.6)
Observations	83	42	72
Number of ID	13	6	11

Table 8: Heterogeneity Analysis

Note: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Mechanism Tests

Mediating Effect of Technology Diffusion

(1)

(1)

VARIABLES	money_firm	Y2
digi	122,094*** (24,132)	1.583*** (0.348)
X2	-2,730 (3,939)	3,295 (19,864)
X4	-327.8 (427.5)	1,626 (1,800)
X12	135.5 (162.8)	-5,929*** (1,151)
X13	36.64 (82.47)	3,534*** (508.4)
X15	-7.084*** (2.202)	-84.44*** (22.30)
X16	102.7*** (15.70)	1,245*** (124.4)
X19	207.6* (114.2)	419.5 (596.6)
X20	-5.192 (10.60)	175.5** (69.73)
X21	5.271 (6.664)	62.73* (32.33)
X22	-16.76 (10.37)	-14.80 (53.97)
X27	33.30*** (9.028)	337.4*** (65.98)
X28	-33.14*** (10.11)	-284.0*** (74.03)
X30	-292.3 (178.1)	-476.7 (989.6)
X31	-61.01 (188.2)	-2,131** (942.1)
Constant	387,803 (401,360)	-1.367e+06 (2.055e+06)
Observations	197	201
Number of ID	30	31

Table 9: Mediating Effect of Technology Diffusion

Note: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Mediating Effect of Financing Accessibility

VARIABLES	(1) valid_invention_patent	(1) Y2
digi	14,104*** (4,998)	16.44*** (2.223)
X2	1,319** (657.6)	-8,510 (17,771)
X4	0.467 (61.04)	931.6 (1,597)
X12	-95.97*** (32.69)	-3,899*** (1,125)
X13	36.85** (15.38)	3,016*** (467.9)
X15	-1.684*** (0.531)	-69.97*** (22.38)
X16	15.47*** (3.157)	1,213*** (120.6)
X19	23.42 (19.40)	108.2 (538.4)
X20	1.875	187.8***

	(2.072)	(63.32)
X21	-0.0402	67.96**
	(1.050)	(29.02)
X22	-2.943*	33.15
	(1.700)	(49.63)
X27	13.29***	219.7***
	(1.762)	(66.94)
X28	-14.13***	-163.8**
	(1.988)	(74.19)
X30	9.627	-384.0
	(30.49)	(908.4)
X31	-71.47**	-1,856**
	(30.35)	(842.2)
Constant	-144,939**	138,933
	(66,879)	(1.839e+06)
Observations	197	201
Number of ID	30	31

Table 10: Mediating Effect of Financing Accessibility

Note: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Conclusions and Policy Recommendations

Based on the research conclusions, this paper proposes the following policy recommendations: Firstly, the development of the digital economy significantly stimulates the comprehensive development of the manufacturing sector. To further promote manufacturing development, it is essential for the government to accelerate the advancement of digital technologies and enhance their integration and application within traditional industries and the real economy. This will facilitate the convergence of digital technologies with traditional industries, thereby improving resource allocation efficiency. Secondly, policymakers should expedite the growth of the digital economy and its integration with traditional industries and the real economy, accelerating the transformation and upgrading of urban manufacturing enterprises. Thirdly, it is imperative for policymakers to enhance the efficient cross-industry allocation of information, data, and technology, driving both industrial and economic digitalization. This involves upgrading the industrial structure, optimizing the allocation of digital technologies and the digital economy across various sectors, and promoting deeper development of urban manufacturing in different regions (Chang et al, 2023).

The empirical evidence demonstrates that the digital economy has contributed to the rationalization and advancement of China's manufacturing sector, aligning with the findings of Liu et al. (2022), Gu et al. (2022), and Zheng et al. (2023). This study expands and innovates upon existing literature in terms of data analysis approaches, research scope, measurement methods, and research content. While foundational studies have utilized city-level panel data analysis, this research advances the analysis to the provincial level, offering a broader perspective on the impact of digital economic development. Furthermore, the research scope extends from the economically developed Yangtze River Delta region, as emphasized in foundational studies, to encompass the entirety of China, providing a more comprehensive understanding of the digital economy's regional impact variances, especially its potential benefits for less-developed areas.

In terms of methodology, while founding literature employs the Theil index to gauge industrial structure rationalization, this study innovatively adopts the Digital Economy Development Comprehensive Index (DEDCI). This comprehensive index more fully captures the impacts of digital economy development across various fields on the rationalization of the industrial structure. Additionally, whereas the foundational literature primarily focuses on the effects of the digital economy on the structure of manufacturing, this study delves deeper by analyzing the specific role of digital economy through quantifying the restructuring of the manufacturing industry.

Lastly, in the realm of innovation and extension, this research specifically examines the effects of the COVID-19 pandemic on the restructuring of industrial structures influenced by the digital economy. The pandemic has expedited digitalization processes, potentially imposing profound impacts on industrial structure adjustments across different regions, thus marking a significant innovative aspect of this study. Through these expansions and innovations, this research offers new perspectives and insights into the rationalization of industrial structures in the digital economy era.

REFERENCES

- [1] Baituova, L., Tleuzhanova, M., & Agipar, B. (2023). *Issues related to human resources development in the conditions of industrial and innovative economy in the Republic of Kazakhstan*. Journal of the Knowledge Economy, 3, 1-13.
- [2] Chang, K., Zhang, H. J., & Li, B. Y. (2023). *The Impact of Digital Economy and Industrial Agglomeration on the Changes of Industrial Structure in the Yangtze River Delta*. Journal of the Knowledge Economy, 15, 9207-9227.
- [3] Chao, C., Gu, J., & Luo, R. X. (2022). *Corporate innovation and R&D expenditure disclosures*. Technological Forecasting and Social Change, 174, 0040-1625.

- [4] Che, S., & Wang, J. (2022). Digital economy development and haze pollution: Evidence from China. *Environmental Science and Pollution Research*, 5, 1-17.
- [5] Chen, X. H., Yan, D., & Chen, W. (2021). *Can the digital economy promote FinTech development?* *Growth and Change*, 11, 1-27.
- [6] Dou, Q. Q., & Gao, X. W. (2022). *The double-edged role of the digital economy in firm green innovation: Micro-evidence from Chinese manufacturing industry*. *Environmental Science and Pollution Research*, 5, 1-19.
- [7] Foster, C., & Azmeh, S. (2019). *Latecomer Economies and National Digital Policy: An Industrial Policy Perspective*. *Journal of Development Studies*, 11, 1-12.
- [8] Guo, F., Wang, J. Y., Wang, F., Kong, T., Zhang, X., & Cheng, Z. Y. (2020). *Measuring the Development of Digital Inclusive Finance in China: Index Compilation and Spatial Characteristics*. *China Economics Quarterly*, 19, 1401-1418.
- [9] Han, D. R., Ding, Y. Y., Shi, Z. Y., & He, Y. (2022). *The impact of digital economy on total factor carbon productivity: The threshold effect of technology accumulation*. *Environmental Science and Pollution Research*, 29, 55691-55706.
- [10] Hao, X. L., Wang, X. H., Wu, H. T., & Hao, Y. (2022). *Path to sustainable development: Does digital economy matter in manufacturing green total factor productivity?* *Sustainable Development*, 31, 360-378.
- [11] He, J. L., Peng, J., & Zeng, G. (2022). *The spatiality of the creative digital economy: Local amenities to the spatial agglomeration of creative e-freelancers in China*. *Journal of the Knowledge Economy*, 10, 1-13.
- [12] Hu, X. Y., & Guo, P. F. (2022). *A spatial effect study on digital economy affecting the green total factor productivity in the Yangtze River Economic Belt*. *Environmental Science and Pollution Research*, 7, 1-19.
- [13] Hu, Y. H., Liu, H., Zhao, J., & Tu, L. P. (2019). *Dynamic analysis of dissemination model of innovation ability of enterprise R&D personnel*. *Physica A: Statistical Mechanics and its Applications*, 531, 0378-4371.
- [14] Jiang, T. (2022). *Mediation Effects and Moderation Effects in Empirical Research on Causal Inference*. *China Industrial Economics*, 5, 100-121.
- [15] Jiang, X. X., Wang, X., Ren, J., & Xie, Z. M. (2022). *Digital economy, agglomeration, and entrepreneurship in Chinese cities*. *Managerial and Decision Economics*, 6, 1-14.
- [16] Kasimova, T., Magomedova, S., & Ismikhonov, Z. (2021). *Econometric models for russia's gdp analysis and forecasting in the industrial section of the economy in conditions of its digital transformation*. *Journal of the Knowledge Economy*, 12(4), 1694-1716.
- [17] Le, T. H., Pham, T. N. H., Nguyen, T. T. H., et al. (2022). *Moderating role of knowledge-sharing on the nexus of digital business and natural resources*. *Journal of the Knowledge Economy*, 11, 1-15.
- [18] Li, J. L., Chen, L. T., Chen, Y., & He, J. W. (2021a). *Digital economy, technological innovation, and green economic efficiency-Empirical evidence from 277 cities in China*. *Managerial and Decision Economics*, 6, 1-12.
- [19] Li, Y., Yang, X. D., Ran, Q. Y., et al. (2021b). *Energy structure, digital economy, and carbon emissions: Evidence from China*. *Environmental Science and Pollution Research*, 28, 64606-64629.
- [20] Meng, F. S., & Zhao, Y. (2022). *How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain*. *Environmental Science and Pollution Research*, 6, 1-19.
- [21] Pyroh, O., Prokopenko, M., Chernobay, L., et al. (2021). *Management of business processes and export-import activity of industrial enterprises in the digital economy*. *Estudios De Economia Aplicada*, 39(5), 1-11.
- [22] Ren, H. Y., & Shi, P. (2009). *An empirical study on the relationship between R&D investment and corporate performance: Based on Data analysis of Shanghai A-share Manufacturing Listed Companies*. *Science and Technology Progress and Countermeasures*, 26, 89-93.
- [23] Schwanholz, J., & Leipold, S. (2020). *Sharing for a circular economy? An analysis of digital sharing platforms' principles and business models*. *Journal of Cleaner Production*, 269(10), 1-12.
- [24] Streltsov, A. V., Yakovlev, G. I., Nikulina, E. Y., et al. (2019). *Ensuring competitive advantage of the industrial enterprises and entrepreneurship in a digital economy*. *Helix*, 9(1), 4753-4757.
- [25] Su, J. Q., Su, K., & Wang, S. B. (2021). *Does the digital economy promote industrial structural upgrading-a test of mediating effects based on heterogeneous technological innovation?* *Sustainability*, 13(8), 1-23.
- [26] Tian, J. T., & Yan, D. L. (2020). *New Infrastructure and Industrial Internet: The 'Road and Vehicle' of Accelerated Digital Economy Post-Epidemic*. *Journal of Shandong University*, 3, 1-8.
- [27] Tian, Z., Li, Y., Niu, X., & Liu, M. (2023). *The impact of digital economy on regional technological innovation capability: An analysis based on China's provincial panel data*. *PLoS One*, 18(7), 0288065.
- [28] Wang, B. C., & Du, C. (2022). *Research on the Characteristics, Influencing Factors and Government Role in Artificial Intelligence Technology Innovation Diffusion: Based on the Data of A-Share Listed Companies*. *Journal of Beijing University of Technology (social sciences edition)*, 22, 142-158.
- [29] Wang, H. N., & Liu, F. S. (2024). *Digital finance and enterprise innovation efficiency: Evidence from China*. *Finance Research Letters*, 59, 1544-6123.
- [30] Wang, L. L., Chen, L. Y., & Li, Y. S. (2021). *Digital economy and urban low-carbon sustainable development: The role of innovation factor mobility in China*. *Environmental Science and Pollution Research*, 29, 48539-48557.
- [31] Wen, J., Yan, Z. J., & Cheng, Y. (2019). *Digital economy and the improvement of regional innovation ability*. *Economic Issues Exploration*, 11, 112-124.
- [32] Wiebe, A. (2017). *Protection of industrial data – A new property right for the digital economy*. *Journal of Intellectual Property Law & Practice*, 12(1), 62-71.
- [33] Wu, G. S. (2000). *Technology Innovation Management*. Tsinghua University Press.

- [34] Wu, Q., Sikandar, A. Q., Rana, Y. H., Hira, I., Kayhan, T., Faiza, S., & Thilini, C. G. (2023). *The effects of enterprises' attention to digital economy on innovation and cost control: Evidence from A-stock market of China*. Journal of Innovation & Knowledge, 8, 2444-569X.
- [35] Yang, X. Q., Shen, Y. Y., & Yin, X. Q. (2017). *Foreign Bank Entry and Corporate Investment Efficiency: Mitigating Financing Constraints or Inhibiting Agent Conflicts?* Journal of Finance and Economics, 43, 97-108.
- [36] Z, Y. G. (1981). *Market value, R&D, and patents*. Economics Letters, 7, 183-187.
- [37] Zhang, X., Wan, G. H., Zhang, J. J., et al. (2019). *Digital Economy, Inclusive Finance, and Inclusive Growth*. Economic Research Journal, 54(8), 71-86.