1. Introduction

As the most dynamic sector of China's economic development, the digital economy is expanding its breadth and depth of integration with all areas of the economy and society and playing an essential role in stimulating consumption (Li et al., 2020), boosting investment (Gu et al., 2021; Yilmaz et al., 2002) and creating employment (Wang et al., 2021a). As the “lubricant” of the domestic economy, the role played by digital finance cannot be ignored. Digital finance is gradually becoming an important driver and growth engine of China's national economy (Li et al., 2020).

In China's pursuit of sustainable economic growth, optimising and upgrading industrial structure is undoubtedly a critical link and an important guarantee for healthy and sustainable economic development (Wang and Wang, 2021) and international trade dynamics (Gozgor, 2014). It is found that export diversification and financial development are critical to upgrading industrial structure (Can and Gozgor, 2018). However, since China's financial development started late and the system is still immature, it is difficult to ensure that small, medium and micro enterprises and farmers can enjoy financial services on demand (Wang and Guo, 2022). Therefore, traditional finance has bottlenecks in serving the real economy and even shows “financial exclusion” (Kling, 2021) and “financial discrimination” effects (Ge and Qiu, 2007). However, the development of digital finance can make up for the lack of traditional financial services, and expand the scope of financial services, thus optimising the allocation of resources, promoting industrial structure upgrading and escorting economic development (Wang and Wang, 2021).

Digital finance is the organic combination of traditional finance and information technology. It has similar characteristics to traditional finance. If the financial development matches the manufacturing, the financial capital will match the industrial capital needed by the real economy (Chauvet and Jacolin, 2017). And this is conducive to the upgrading and optimization of industrial structure. However, excessive financial development will also lead to some potential problems. For example, abnormal financial development and immoderate speculation will lead to excessive financialization of the real economy and industrial hollowing out (Ren et al., 2023a; Webber, 2001). This evidence is not beneficial to industrial structure upgrading. Therefore, the relationship between digital finance and industrial structure upgrading is related to the level of financial development. Understanding the causality of digital finance and industrial structure in China's current stage will help improve the economic environment and optimize the industrial layout.

Previous studies analyze the correlation between the digital economy and economic factors such as the urban-rural income gap and rural residents' income (Seya et al., 2012), employment and entrepreneurship (Weiler, 2000), and green innovation (Zhang and Liu, 2022; Ren et al., 2023b) mainly from a macro perspective. Alternatively, they approach the financial industry's perspective to analyze the impact of digital economy development on the efficiency and risk behaviour of financial institutions such as the banking and insurance industries (Lu et al., 2022; Chauvet and Jacolin, 2017; Ren et al., 2022a). The study on the causality of digital finance and industrial structure is insufficient. In terms of variable selection, previous scholars mainly measured the level of the digital economy through self-constructed indicators (Ma and Zhu, 2022), which are measured in a crude statistical calibre and not refined to financial development. The digital financial inclusion index this study chooses is the statistics of China's largest financial service platform, Ant Financial Services, which can accurately measure each city's digital financialization level (Guo et al., 2020). Regarding the choice of research methods, scholars mostly use ordinary panel regression analysis (Luo and Li, 2022), ignoring the possible spatial spillover effects. This study fills the gaps and shortcomings of previous studies on digital finance.

First, the theoretical framework is constructed by combing through previous literature. The core question this study focuses on is whether the development of digital finance in China can promote upgrading industrial structure. We investigate this question using the “Digital Financial Inclusion Index of China (DFIIC)” published by the Digital Finance Center of Peking University (Guo et al., 2020). The industrial structure upgrading index is chosen to construct a two-way fixed effects model for the benchmark regression. The results demonstrate that digital finance can effectively stimulate industrial structure upgrading. Additionally, this study investigates the practical results of the sub-indicators of the digital finance index separately. The results show that the breadth of coverage exhibits the most prominent effect on industrial structure relative to depth and digitization.

In the benchmark regressions, the cities are analyzed individually to obtain the average influence of digital finance. However, according to the first law of geography (Tobler, 2004), “everything is connected to everything else, but things closer together are more connected than things farther away". The interactions between cities may also determine the effect of digital finance (Su et al., 2021b). To this end, a spatial econometric model is employed to study the spatial spillover effects of digital finance on industrial structure. The results show that the industrial structure upgrading shows a significant positive spillover effect, which means that the industrial structure upgrading of peripheral cities can effectively stimulate local industrial upgrading.

At this point, this study has made it clear that industrial structure upgrading can be stimulated by digital finance. But what factors influence the effectiveness of digital finance? A heterogeneity analysis is conducted to answer this question. We conduct a sub-sample analysis in three dimensions: the average income level, the degree of financialization, and the urban-rural earnings inequality (Luo and Li, 2022). Heterogeneity analysis reveals that digital finance plays a more significant role in cities with developed economies, low levels of financialization, and small urban-rural income gaps. It also proves the vital role of the breadth of coverage of digital finance for economically backward regions.

Furthermore, to demonstrate the accuracy of the benchmark results, this study ran regressions using the government's attention allocation (Xu et al., 2022) to different industries as a proxy for industrial structure upgrading. It turns out that the government's attention to the tertiary industry has increased significantly as digital finance expands, which corroborates the benchmark findings. Besides, to analyze the dynamic effect of industrial structure upgrading, the systematic Generalized Method of Moments (GMM) (Wang and Wang, 2021) are employed to conduct dynamic panel regression analysis. This evidence further confirms that digital finance can positively influence industrial structure upgrading.

Based on the above empirical analysis, it can be concluded that industrial structure and digital finance causality exist in Chinese cities. Then furthermore, how does digital finance affect industrial structure optimization? Referring to the study of Ma and Zhu (2022), this study tests the mechanism of urban innovation and entrepreneurship and finds that it exhibits a partial mediating effect. In addition, the residential consumption structure is proposed as a possible influence mechanism through theoretical analysis.

Based on the above empirical results, the findings are summarized as follows: (1) industrial structure upgrading can be promoted mainly by digital finance in Chinese cities, and these findings remain valid after robustness tests. (2) both digital finance and industrial structure exhibit significant spatial spillover effects. (3) Digital finance can indirectly influence industrial structure upgrading through innovation, entrepreneurship, and household consumption. (4) The coverage plays the most significant role among the various sub-indicators of digital finance. (5) The influence of digital finance is more significant in cities with more developed economies, less financialization and lower earning disparity.

This paper's main innovations and contributions are as follows. Firstly, in addition to the traditional industrial structure upgrading index, this study also investigates the allocation of government attention to different industries under the influence of digital finance. The data of government attention are obtained from the textual analysis of government work reports. This analysis complements the measurement perspective on industrial structural upgrading and explores the correlation between digital finance and government attention. Secondly, this study explores the mediating effect of household consumption structure by using data from the micro consumption domain. Most previous studies have analyzed the mechanism in terms of the market size (Jia et al., 2021), entrepreneurial activity (Nambisan et al., 2019) and green innovation index (Ma and Zhu, 2022). We increase the plurality of research perspectives on this question from a microscopic perspective. Thirdly, this study discovers that the coverage breadth of digital finance plays the most prominent role. This paper suggests that the government and relevant departments should expand the coverage of digital infrastructure as much as possible better leverage digital finance's function in alleviating income inequality. Fourth, this paper explores the mutual influence of different cities and finds that digital finance and industrial structure upgrading show significant spatial autocorrelation effects. This evidence suggests that the government can fully play to neighbouring cities' synergy to optimize regional industrial structure.

The paper's outline is as follows. Section 2 demonstrates the theoretical framework and presents the research hypotheses of the paper. Section 3 describes the models, the data and the methodology. Section 4 discusses the results and provides several robustness checks. Section 5 concludes the study and makes policy recommendations.

2. Theoretical framework and hypotheses

This section constructs a conceptual framework between digital finance and industrial structure. Fig. 1 demonstrates the conceptual framework and research hypotheses of this paper.

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Fig. 1. The conceptual framework of digital finance on industrial structure upgrading.

Notes: The framework diagram includes this study's main research questions and hypotheses.

2.1. The influence of digital finance on industrial structure upgrading

Some scholars investigate the relationship between traditional financial development and industrial structure upgrading and find that financial development is crucial to optimising industrial structure (Wang et al., 2021a; Wang and Wang, 2021). However, current financial support is mainly directed to large enterprises with high market share. And the financial services that small, medium and micro enterprises and farmers can obtain are still complex to meet their needs. Digital finance, combining conventional finance and high-tech digital technology, can effectively facilitate enterprise financing channels, accelerate innovation and entrepreneurship, and thus influence macroeconomic development. In particular, it can reduce information asymmetry, lower transaction costs, help realize transaction disintermediation and optimize resource allocation (Li et al., 2020).

Theoretical studies show that digital finance improves the coverage of financial services and optimizes the allocation of capital among industries, thus promoting the upgrading of industrial structure (Su et al., 2021a; Yuan et al., 2021; Ren et al., 2022b). Most existing literature supports that "industrial structure upgrading can be largely promoted by digital finance" (Su et al., 2021a). However, some studies show that financial development inhibits the optimization of industrial structures (Wang et al., 2021a). Therefore, only by verifying the causality of digital finance and industrial structure upgrading in combination with the actual situation in China can authorities put forward the development strategy of digital finance in a more targeted way.

China's financial development started relatively late, and the degree of market financialization has not reached the level of developed countries (Lu et al., 2022). The financial system and financial supervision are still improving. Therefore, this paper proposes the conjecture:

Hypothesis 1

Digital finance development can significantly contribute to industrial structure upgrading.

2.2. Mechanisms analyses between industrial structure upgrading and digital finance

Digital finance can foster more entrepreneurial opportunities through channels such as influencing market size, knowledge spillover and factor combinations (Baker, 2021).

Besides, the expansion of digital finance can create a more fluid financing environment for enterprises, especially in technology-intensive and innovative industries, thus improving urban innovation and entrepreneurship (Nambisan et al., 2019).

Moreover, the improved level of urban innovation and entrepreneurship stimulates the adjustment of industrial structure. Entrepreneurial activity is an endogenous driver of economic growth and plays a significant role in job creation (Thurik, 2003), industrial upgrading and structural transformation (Nambisan et al., 2019). Innovation and entrepreneurship can promote the rationalization of market resource allocation and the progress of technology-intensive and innovation-intensive industries. Accordingly, another hypothesis is proposed as follows.

Hypothesis 2a

Digital finance can promote industrial structure upgrading by boosting innovation and entrepreneurship in cities.

Digital finance not only affects the innovative behaviour of firms but also impacts the consumption of households and individuals. Li et al. (2020) find that digital finance substantially boosts household consumption. Digital finance mainly influences the residents' consumption of health care, education, and recreation, i.e., expenditures on service goods. Microeconomic theories conclude that consumer purchasing will impact the product market, affecting the industry structure (Luo and Li, 2022). Therefore, this paper argues that digital finance influences industrial structure upgrading by adjusting residents' consumption structure.

Hypothesis 2b

Digital finance can indirectly influence the industrial structure by adjusting the residents' consumption.

2.3. Spillover effects of industrial structure upgrading and digital finance

One important feature of digital finance is that it compresses the distance in time and space through efficient information transmission and reduces the cost of access to financial services for the public, thus enhancing the breadth and depth of inter-regional economic activity linkage. Several scholars have studied the spillover effects of digital finance. Wang and Guo (2022) investigate the causality of digital finance and carbon emissions. Zhang and Liu (2022) explore the relationship between digital finance and green technology innovation using the spatial econometric method. In addition, researchers also verify the spatial spillover effects of digital finance and analyze the impact of digital finance on economic growth (Ding et al., 2022) and urban ecological efficiency (Su et al., 2021b). In addition, the local industrial structure will also be influenced by the progress of industrial structures in the peripheral area. This evidence indicates the spatial autocorrelation effect of industrial structure (Cheng et al., 2018; Zhang et al., 2020; Song et al., 2021; Ren et al., 2022c).

We alleviate the bias caused by omitted variables and assume that the spatial spillover effect for industrial structure upgrading and digital finance exists. Spatial autocorrelation testing can be adapted to verify this assumption (Elhorst, 2014). The SAR model and SDM are adopted to discover the spillover effect of digital finance on industrial structure (Lv et al., 2019).

Hypothesis 3

Local industrial structure upgrading can be influenced by the digital finance of peripheral cities via spatial spillover.

2.4. Heterogeneity analyses

Different cities differ primarily in terms of economic growth, resource superiority, affluence, and demographic environment. This paper use heterogeneity analysis to explore how the role of digital finance differs in different cities. Most scholars have conducted sub-sample discussions by distinguishing geographical locations (Ma and Zhu, 2022; Jia et al., 2021). This is because China's economic pattern exhibits "backwards in the middle and west and developed in the east". This paper analyzes the impact of economic growth by directly dividing the sample into high and low groups. In addition, digital finance is based on traditional finance. Digital finance exhibits different roles at different levels of financial development.

Meanwhile, digital finance is inclusive and improves income inequality (Luo and Li, 2022). Therefore, this paper analyzes how digital finance functions differently in cities with different urban-rural income disparities. Reasonably, the following hypothesis is propounded.

Hypothesis 4

Digital finance has heterogeneous impacts on industrial structure upgrading.

3. Model, data and methodology

3.1. Model

We refer to Ma and Zhu (2022) to construct the following model to explore the impact of digital finance on industrial structure upgrading : (1)$Isu_{it}=\alpha_0+\alpha_1 Dif_{it}+\alpha_c X_{it}+\mu_i+\delta_t+\varepsilon_{it}$

where Isu_{it} is the industrial structure upgrading index of the city i in year t, Dif_{it} is the level of digital finance of city i in year t, and vector X_{it} denotes the set of control variables; μ_i denotes the individual fixed effects of the city i that do not vary over time, while δ_t controls for time-fixed effects; and ε_{it} denotes the random disturbance term.

In addition to the direct effect captured by Eq. (1), this research investigates the mechanism of digital finance's effect on industrial structural upgrading. This study focuses on testing whether urban innovation and entrepreneurship level ($Innovation_{it}$) and consumption structure of residents ($Consume_{it}$) are the mediating variables ($Mechan_{it}$). The specific testing steps are as the following. First, check if Dif_{it} has a significant impact on Isu_{it}, i.e., whether the coefficient α_1 is significant. Second, construct a linear regression of Dif_{it} on the mediating variable $Mechan_{it}$, as shown in Eq. (2). Third, construct a regression of Dif_{it} and $Mechan_{it}$ on Isu_{it}, as shown in Eq. (3). The significance of the regression coefficients of β_1, γ_1, and γ_2 are used to determine the existence of mediating effects. The specific settings of the models are as follows:(2)$Mechanism_{it}=\beta_0+\beta_1 Dif_{it}+\beta_c X_{it}+\mu_i+\delta_t+\varepsilon_{it}(3)Isu_{it}=\gamma_0+\gamma_1 Dif_{it}+\gamma_2 Mechan_{it}+\gamma_c X_{it}+\mu_i+\delta_t+\varepsilon_{it}$

where $Mechan_{it}$ denotes the mediating variable (including $Innovation_{it}$ and $Consume_{it}$) of the city i in year t, and other variables have the same meaning as Eq. (1).

Finally, the spatial lag terms of the variables are introduced into the benchmark model (You and Lv, 2018), thus obtaining the spatial panel model:(4)Isuit=α0+ρWIsuit+α1Difit+φ1WDifit+αcXit+φcWXit+μi+δt+εitwhere ρ denotes the spatial autoregressive coefficient, W implies the spatial weighting matrix, and wij is an element of the spatial weighting matrix reflecting the proximity of city i and city j. We select the geographic distance matrix, the economic matrix and the adjacency matrix (Qu and Lee, 2015) to construct the spatial model to accurately measure the spillover effect. φ1 and φc are the elasticity coefficients of the spatial lag terms of Dif and the control variables, respectively. Equation (4) contains the spatial lag terms of the explained and explanatory variables and is called the spatial Durbin model (SDM). When φ1 and φc are both equal to zero, the SDM model degenerates to the spatial autoregressive model (SAR) (Elhorst, 2014).

3.2. Variables

Based on the necessity to test the research hypotheses, the variables used in the models are defined as follows.

3.2.1. Dependent variable

The explained variable of this study is industrial structure upgrading which implies the change in industry and efficiency improvement. Generally speaking, economic evolution is usually accompanied by a continuous increase in the share of the tertiary sector. Therefore, this study structures an industrial structure upgrading index by referring to the studies of Du et al. (2021) and Xu et al. (2022). The following formula measures the index: (5) $Isu=\sum_{i=1}^{3} I_i \times i = I_1 + I_2 \times 2 + I_3 \times 3$

where I_i denotes the ratio of the output value of industry i to GDP.

Generally speaking, in the long-term evolution of the industrial structure, the output value of the primary industry remains relatively stable. The secondary industry increases and then decreases, while the output value of the tertiary industry increases with the maturity of economic development (Fisher, 1935). Therefore, this index Isu can measure industrial structure upgrading. The larger the Isu values, the more developed the industrial structure is.

On the other hand, the influence of Dif on industrial structure will be exerted not only through market transmission mechanism but also through government macro regulation (Yuan et al., 2021). The government's attention allocation to different industries is the direction of possible adjustment of industrial structure in the future (Cheng et al., 2021). Therefore, studying the influence of digital finance on government attention helps to study industrial structure through the lens of government and enriches the research on this topic. Government attention can be obtained from government work reports (Zhang et al., 2021).

According to Bao and Liu (2022), using the LDA model, this study first extracts the government's attention for “industrial structure” from 289 prefectural-level city reports. Second, this study sub-words and categorizes words related to industrial structure with word frequency analysis. Then, the alternative proxy variable for the dependent variable, Isu_govern, is constructed. Based on this data, the correlation of digital finance and industrial structure is investigated through the lens of government.

The division of related words for different industries is shown in Table 1. We calculate the share of keywords of different industries among all keywords of the industrial structure to construct Isu_govern, which implies industrial structure upgrading from the local government perspective. Similar to Eq. (5), the Isu_govern is set as follows.

$$Isu\_govern=\sum_{i=1}^{3} Attention_i \times i = Attention_1 \times 1 + Attention_2 \times 2 + Attention_3 \times 3 \tag{6}$$

Table 1. The division of related words for different industries.

Mechanism variable	Industry	Related words
Local government attention (Govern)	Primary industry (Prim)	Rural, farmers, agriculture
	Secondary industry (Seco)	Industry, processing, manufactur
	Tertiary industry (Tert)	Tourism, tertiary industry, digita

Notes: The related words are filtered out by high-frequency word analysis. The distribution of government attention to different industries also serves as a proxy variable for industrial structure upgrading through the lens of government.

where $Attention_i$ denotes the level of government attention to industry i.

For instance, the level of government attention to the primary sector is reflected by the number of times “rural”, “farmers”, and “agriculture” are mentioned in the government work report (i.e., word frequency). And the government's attention to “industrial structure” can be obtained by aggregating the word frequencies of all the related words in Table 1.

3.2.2. Main variable of interest

Digital finance (Dif) is the key independent variable of this paper. This paper uses the "Digital Financial Inclusion Index" of Peking University (Guo et al., 2020) to measure digital financial development. The index is subdivided into three secondary indicators, including coverage breadth (Bread), depth of usage (Depth) and degree of digitalization (Digit). The index system is shown in Table 2.

Table 2. The index system of digital finance.

Primary indicators	Secondary indicators
Digital Financial Inclusion Index (Dif)	The breadth of coverage (Bread)
	Depth of usage (Depth)
	Degree of digitalization (Digit)

Primary indicators	Secondary indicators

Note: In this paper, the general index of digital finance Dif and three secondary indexes: Bread, Depth, and Digit are mainly used for analysis.

3.2.3. Control variables

The average wage of employees (Wage). The employees' annual average salary (in CNY) will be logarithmically processed to obtain the proxy variable of residents' income. Household income can influence consumption, affecting industry structure (Zimmerman, 1932; Ogaki, 1992).

Level of Urbanization (Urban). As China's urbanization process accelerates, residents' consumption is also being upgraded, further influencing the industrial structure (Wang et al., 2016). This paper selects the population density of cities (in 10,000 people per square kilometre) to measure urbanization.

Degree of fiscal decentralization (Fiscal). The degree of fiscal decentralization reflects the local government's ability to dominate its finances. It can also reflect local government intervention in the market (Wang et al., 2021b). The share of local government general budget expenditure in GDP (in %) is selected to measure the fiscal decentralization index.

International Internet penetration (Inter). The Internet is the underpinning of the digital economy. It is an essential determinant in measuring its development and an important innovation in changing business models and consumer habits (Asongu et al., 2017). The number of international Internet users (in 10,000 households) is chosen as a proxy variable for Internet penetration.

Unemployment level (Unemp). The unemployment rate is essential in observing economic and financial development and predicting the direction of industrial restructuring (Weiler, 2000). This study selects the logarithm of the unemployed population (10,000 people) to measure the unemployment level.

3.2.4. Mechanism variables

Urban innovation and entrepreneurship level (Innovation): This study refers to the innovation and entrepreneurship index of Chinese cities constructed by Peking University and demonstrates urban innovation and entrepreneurship in terms of the number of newly registered enterprises, the number of patents granted, etc. (Ma and Zhu, 2022). The index system is exhibited in Table 3.

Table 3. The index system of innovation.

Index	Indicators (weight)	Measurement
Innovation	New Businesses (20%)	Number of new business registration
	Attracting foreign investment (15%)	Number of new foreign corporate in
	Attracting venture capital investment (25%)	Number of new venture capital inves
	Number of patents granted (25%)	Number of new invention patents gra
		Number of new utility model patents
		Number of new design patent disclos

Index	Indicators (weight)	Measurement
	Number of trademark registrations (15%)	The number of new trademark regist

Notes: The index system and data are from the National Institute of Development, Peking University. The variable Innovation generated by the index system will be included in the model for research as a mechanism variable.

Consumption structure of the residents (Consume): This paper analyzes the structure of residents' consumption concerning Li et al. (2020). Household expenditures on agricultural products (primary industry) are defined as household expenditures on food. Household consumption expenditure on industrial goods (secondary industry) is defined as the sum of expenditure on housing and household goods and services. The remaining five significant categories of expenditures are defined as household expenditures on services (tertiary industry). We use the ratio of household expenditures in the tertiary sector to those in the secondary sector to express the consumption structure (Consume).

$$Consume_{it} = \frac{Household\ expenditure\ on\ tertiary\ industry_{it}}{Household\ expenditure\ on\ secondary\ industry_{it}} \tag{7}$$

3.2.5. Methodology: spatial weight matrix

An essential element in the spatial econometric models is the spatial weighting matrix. It describes the relative position of different research objects geographically or economically (Elhorst, 2014). According to the different ways of the composition of the elements in the matrix, the spatial weight matrix is classified into adjacency matrix, geographic matrix, economic matrix, economic geography matrix, etc. The elements of the different matrices are specified as follows, and dij is the geographic distance between city i and city j calculated by their latitudes and longitudes.

The elements of the adjacency matrix (W1) are shown in Eq. (8):(8)wij={1,dij<120,dij≥12

The elements of the geographic matrix (W2) are shown in Eq. (9):(9)wij={1diji≠j0,i=j

The elements of the economic matrix (W3) are shown in Eq. (10):(10)wij={1|avpgdpi−avpgdpj|i≠j0,i=jwhere avpgdpi is the average GDP per capita of city i during 2011–2020, and |avpgdpi−avpgdpj| measures the economic gap between the two cities.

3.3. Data

The data sources and statistical characteristics of all the above variables are summarized in the section.

3.3.1. Data sources

Since the digital finance index started in 2011, a data set of 289 Chinese prefecture-level cities from 2011 to 2020 has been selected to construct a city-year panel. The digital financial index in the study comes from Peking University (Guo et al., 2020), and the government attention data comes from the government work report. All other variables in the models are sorted from the China City Statistical Yearbook. For variables measured in terms of prices, they are uniformly deflated to constant 2011 prices using the GDP deflator of each province each year. For missing values in the statistics, this study uses linear interpolation to complement the missing values.

3.3.2. Descriptive statistics

The summary statistics of the main variables are exhibited in Table 4. The results show that the magnitude of all variables remains at comparable levels with no significant outliers. Among them, the mean value of industrial structure upgrading (Isu) is 1.035, the maximum value is 1.792, the minimum value is 0.162, and the standard deviation is 0.204. These statistics indicate that the industrial structure upgrading index differs prominently among cities. The digital financial index also shows "small mean value and large standard error" characteristics. Regarding control variables, there are also significant differences among prefecture-level cities.

Table 4. Descriptive statistics.

Empty Cell	Variable	Obs.	Mean	Std. Dev.
Dependent variable	Isu	2890	1.035	0.204
	Isu_govern	2890	1.694	0.222
Key explanatory variable	Dif	2890	1.743	0.683
	Bread	2890	1.649	0.674
	Depth	2890	1.713	0.698
	Digit	2890	2.108	0.824
Control variables	Fiscal	2890	0.210	0.129
	Urban	2890	0.044	0.035

Empty Cell	Variable	Obs.	Mean	Std. Dev.
	Inter	2890	4.195	0.963
	Wage	2890	10.91	0.334
	Unemp	2890	1.097	0.571
Mechanism variables	Innovation	2344	0.502	0.289
	Consume	2055	1.752	0.578
Heterogeneity analysis	Economy	2890	1.728	0.473
	Finance	2870	2.431	1.109
	Theil	2070	0.080	0.041

Notes: The magnitude of all variables remains at comparable levels with no significant outliers. The unit of Isu and Isu_govern is %. Digital financial indicators are all divided by 100 to make the data comparable. The share of local government general budget expenditure in GDP (in %) is selected to measure the fiscal decentralization index (Fiscal). This paper selects the population density of cities (in 10,000 people per square kilometre) to measure the level of urbanization (Urban). The number of international Internet users (in 10,000 households) is chosen as a proxy variable for Internet penetration (Inter). The annual average wage (in CNY) of employed workers is selected to be logarithmically processed to obtain the proxy variable of residents' income (Wage). We choose the logarithm of the unemployed population (in 10,000 people) to measure the unemployment level (Unemp).

4. Results and discussion

A series of empirical analyses are conducted to investigate the causality of digital finance and industrial structural upgrading. In this section, the empirical results are analyzed and discussed in detail.

4.1. Benchmark results

This paper estimates the causality of digital finance on industrial structure upgrading according to Eq. (1). Table 5 reports the linear estimation results with two-way fixed effects. Models (1)–(4) estimate the influence of different indicators of digital finance on Isu without considering control variables. However, models (5)–(8) are estimated when considering control variables.

Table 5. Benchmark results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Isu	Isu	Isu	Isu	Isu	Isu
Dif	0.222***				0.144***	
	(4.13)				(2.72)	
Bread		0.236***				0.155**
		(3.79)				(2.53)
Depth			0.080**			

			(2.41)			
Digit				0.022**		
				(2.31)		
Fiscal					−0.286**	−0.282**
					(-2.53)	(-2.45)
Urban					1.768**	1.857**
					(2.07)	(2.15)
Inter					−0.004	−0.008
					(-0.57)	(-1.04)
Wage					0.055*	0.050*
					(1.90)	(1.78)
Unemp					0.014	0.013
					(1.41)	(1.23)
Constant	0.648***	0.646***	0.897***	0.990***	0.165	0.232
	(6.91)	(6.30)	(15.74)	(50.32)	(0.49)	(0.71)
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.860	0.860	0.857	0.857	0.869	0.869
N	2890	2890	2890	2890	2890	2890

Notes: The above are regression results based on the fixed effects model. Columns (1)–(4) represent the estimation results without considering the control variables. Whereas columns (5)–(8) are the results based on the full model (Eq. (1)). According to the regression coefficients of Dif, Bread, Depth and Digit, industrial structure upgrading can be substantially boosted by digital finance. Among the sub-indicators of digital finance, the breadth of coverage plays the most significant role. Besides, inside the brackets in the table are the t-statistics, and *** means p-value <0.01, ** denotes p-value <0.05, * implies p-value <0.1.

First, from the regression coefficients of Dif in models (1) and (5), it's clear that digital finance, in general, can substantially boost Isu. Therefore, **Hypothesis 1** holds. Specifically, this promotion effect mainly credits to the coverage breadth (Bread). The absolute value and significance of the coefficients of Bread are much higher than those of Digits and Depth. Furthermore, digitization plays a more significant role (higher significance level) in reshaping the industrial structure relative to depth. Therefore, local governments should focus more on expanding the coverage and accelerating the digitization process to escort digital finance development.

Moreover, control variables in models (5)–(8) exert different influences on Isu, and the degree of government decentralization has a prominent negative influence (−0.286) on Isu. This evidence indicates that the stronger the government's ability to dominate finances, the more the industrial structure will be tilted toward primary and secondary industries. In contrast, the development of tertiary industries lags relatively behind. This phenomenon mainly occurs in resource-based cities and the early stage of urban development (Wang et al., 2021a). With the establishment of the market order and the improvement of the system, economic development will reach a higher level. Government intervention and regulation are weakened, while the labour force and commerce gather in cities. This issue creates conditions for the progress of the tertiary industry (Weiler, 2000). Based on this reality, the industrial structure will be upgraded along with the process of urbanization, which is also proved in the regression coefficient of Urban (1.768). In other words, the development of urbanization can substantially contribute to industrial structure upgrading.

Research shows that the proportion of users of digital retail finance across all channels continues to grow. The 2022 China Digital Finance Survey Report points out that as banks' digital transformation picks up speed, the proportion of online financial services is growing by leaps and bounds. This real-world evidence shows that the development of digital finance does not stop at the top-level architecture but is gradually becoming an important engine to pull the economy's high-quality economic growth.

4.2. Mediating effect analyses

This section will empirically analyze the influence mechanism discussed in the previous theoretical analysis section through an empirical study. We test whether Dif indirectly facilitates industrial structural upgrading through Innovation and Consume (Hypothesis 2a and 2b). Before conducting the mechanism test, it was verified that the core explanatory variable significantly affects the dependent variable based on Eq. (1), as shown in column (1). The mediation test is divided into two steps. First, based on Eq. (2), test whether the core explanatory variable can affect mechanism variables prominently. Second, the synergistic effect of the core explanatory variable and mechanism variables on the explained variable is investigated according to Eq. (3). Columns (2) and (3) in Table 6 show the results of the two-step regression to test the mediating effect of Innovation, respectively, while columns (4) and (5) test whether there is a mediating effect of consumption structure.

Table 6. Mechanism test results.

	(1)	(2)	(3)	(4)
	Benchmark	Step 1	Step 2	Step 1
	Isu	Innovation	Isu	Consume
Dif	0.222***	0.092***	0.077**	−0.259***
		(2.61)	(2.39)	(-2.67)
Innovation			0.043*	
			(1.89)	
Consume				

Constant	0.648***	0.005	−0.183	1.399**
		(0.02)	(-0.49)	(2.32)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R2	0.860	0.942	0.923	0.948
N	2890	2272	2272	2010

Notes: Column (1) is the result of the benchmark regression, which proves that industrial structure upgrading can be promoted mainly by digital finance, and the total effect of Dif on Isu is 0.222. Columns (2) and (4) demonstrate the impact of Dif on mechanism variables. Columns (3) and (5) illustrate the synergistic influence of Dif and mechanism variables on Isu. By comparing the absolute value and significance of the above coefficients, it can be proved that urban innovation, entrepreneurship, and household consumption structure partially mediate. Besides, inside the brackets in the table are the t-statistics, and *** means p-value <0.01, ** denotes p-value <0.05, * implies p-value <0.1.

From Table 6, it can be found that Dif can prominently facilitate urban innovation and entrepreneurship (β1=0.092***). In column (3), the regression coefficients of both Dif and Innovation on Isu are significantly positive (θ1=0.077**; θ2=0.043*).

The coefficient of digital finance decreases from 0.092 to 0.077. This result reveals that innovation and entrepreneurship exhibit a partial mediation effect. Thus, **Hypothesis 2a** is verified to be valid. Moreover, the total effect of Dif on Isu is 0.222, of which the direct effect is 0.077.

Similarly, it can be found from column (4) that the influence of Dif on the consumption structure mainly lies in the consumption of industrial goods (secondary sector). Compared to the consumption of services (tertiary sector), the process of Dif contributes more to the escalation of industrial consumption. Comparing the coefficients of Dif in columns (1) and (5), it's clear that the average impact of Dif on Isu decreases from 0.222 to 0.173, indicating that consumption structure plays a part of the mediation effect. This evidence demonstrates that **Hypothesis 2b** is valid.

4.3. Spatial spillover effects

To investigate the possible spatial spillover effects between Dif and Isu, this study selects the SAR model and SDM to conduct spatial panel regression analysis. Meanwhile, to alleviate the bias brought by matrix selection, this study constructs the spatial econometric models with the adjacency matrix (W1), geographic matrix (W2) and economic matrix (W3), respectively. Before conducting the regression analysis, this study first verifies whether the spatial autocorrelation effect, a prerequisite of the spatial econometric model, exists.

4.3.1. Spatial autocorrelation test results

The spatial autocorrelation effect refers to the mutual influence of variables from different cities. For example, local air pollution is influenced not only by local economic factors but also by the air quality of neighbouring places. Therefore, it can be concluded that air pollution exhibits a spillover effect. Scholars usually use Moran's Index to measure spatial autocorrelation (Debarsy and Ertur, 2010). Moran's Index is calculated by the following Eq. (11).

$$(11)\quad Moran'sI=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(X_i-\bar{X})(X_j-\bar{X})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}}$$

where W_{ij} is the spatial weighting matrix, and $\bar{X}$ and $S2$ are the mean and variance of the variable, respectively.

We mainly focus on the spillover effects of industrial structure and Dif. First, this study selects the years 2011, 2014, 2017 and 2020 according to the average interval. Then the global Moran's Indices of the two variables are calculated separately in these years, and the results are shown in Table 7. We choose the geographic matrix (W2) to measure the spatial autocorrelation effect. The results show that both Isu and Dif demonstrate prominent spatial autocorrelation.

Table 7. Global Moran's index of Isu and Dif in some years.

Variable	I	Z
Isu_2011	0.022***	4.141
Isu_2014	0.027***	4.891
Isu_2017	0.027***	4.952
Isu_2020	0.029***	5.290

Variable	I	Z	[illegible]
Dif_2011	0.116***	19.355	[illegible]
Dif_2014	0.106***	17.704	[illegible]
Dif_2017	0.128***	21.363	[illegible]
Dif_2020	0.169***	28.009	[illegible]

Notes: Index I means global Moran's Index. P-value reflects the significance of the spatial autocorrelation coefficient. The P-values of all the global Moran's Indices in the above table are much less than 0.01, indicating that the digital finance indices and industrial structure upgrading indices in different years show a significantly positive spatial autocorrelation effect.

Fig. 2, Fig. 3 show the local Moran's scatter plots of industrial structure and digital finance, respectively. In more detail, we demonstrate the spatial correlation of different regions, reckon the local Moran Indices of these two variables in 2011, 2014, 2017, and 2020 and draw local Moran's scatter plots. The figures show that the scatters mainly gather in the first and third quadrants, showing positive spatial autocorrelation. This follows the global Moran's Index analysis findings, signifying that the spatial econometric model's preconditions hold (Elhorst, 2014).

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Fig. 2. Scatter graph of the local Moran's index of Isu in 2011, 2014, 2017, and 2020.

Notes: The scatter plot is based on the local Moran’s Index of industrial structure upgrading index of 289 cities in 2011, 2014, 2017 and 2020. The graph shows the spatial autocorrelation of . This evidence indicates that exhibits prominent spatial autocorrelation.

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Fig. 3. Scatter graph of Moran's index of Dif in 2011, 2014, 2017, and 2020.

Notes: The scatter plot is based on the local Moran's Index of digital finance index of 289 cities in 2011, 2014, 2017 and 2020. The graph shows the spatial autocorrelation of . And the slope of the fitted line of the regression in the graph is significantly positive. This evidence indicates that demonstrates prominent spatial autocorrelation.

4.3.2. Spatial regression results

Table 8 demonstrates the estimation results. Models (1)–(4) are constructed based on the SAR model and adjacency matrix, while models (5)–(8) are based on SDM and adjacency matrix. First, the results of the spatial regressions are consistent with the benchmark regressions, and Isu can be substantially promoted by digital finance. (0.182*** and 0.090***). In addition, rho is significantly positive in all regressions, denoting that Isu exhibits prominently positive spillover effect. The industrial structure upgrading in peripheral regions can accelerate the local industrial structure upgrading. Furthermore, digital finance in peripheral regions negatively impacts local industrial structure upgrading. This evidence may be the result of relocating local industries to neighbouring cities.

Table 8. Spatial regression results without control variables.

	SAR (W1)				SDM (W1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Main						
Dif	0.182***				0.090***	
	(6.75)				(3.33)	
Bread		0.204***				0.073***
Empty Cell		(7.41)				(2.89)
Depth			0.061***			
			(3.48)			
Digit				0.015**		

				(2.08)		
Constant					0.192***	0.208***
					(4.79)	(4.82)
Wx						
Dif					−0.113***	
					(-4.09)	
Bread						−0.100***
						(-3.86)
Depth						
Empty Cell						
Digit						
Spatial						
rho	0.570***	0.589***	0.631***	0.645***	0.847***	0.835***
	(7.69)	(8.13)	(9.07)	(9.44)	(28.65)	(26.06)
Variance						

lgt_theta					−1.710***	−1.716***
					(-32.31)	(-31.84)
sigma2_e	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(37.97)	(37.96)	(37.95)	(37.95)	(35.90)	(35.82)
Controls	No	No	No	No	No	No
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.246	0.255	0.230	0.209	0.216	0.215
N	2890	2890	2890	2890	2890	2890

Notes: Columns (1)–(4) display the regression results of the SAR model. The coefficients for all indicators of digital finance are significantly positive and consistent with the benchmark results. Besides, inside the brackets in the table are the t-statistics, and *** means p-value <0.01, ** denotes p-value <0.05, * implies p-value <0.1.

Furthermore, this study includes the control variables used in the benchmark regression in the spatial model. It selects the SAR model for the regression. Table 9 shows the estimation results of the spatial panel. For brevity and ease of understanding, this paper only shows the regression results for Dif and Bread. From the empirical results, industrial structure upgrading can be primarily promoted by digital finance when spatial spillover effects are considered. This finding confirms **Hypothesis 3**.

Table 9. Spatial panel regression results.

	SAR (W1)		SAR (W2)		SAR (W
	(1)	(2)	(3)	(4)	(5)
Main					
Dif	0.115***		0.098***		0.064**
	(4.30)		(3.77)		(2.51)
Bread		0.134***		0.057**	
		(4.87)		(2.18)	
Spatial					
rho	0.463***	0.480***	2.060***	5.864***	0.486**
	(5.90)	(6.23)	(19.79)	(102.01)	(17.83)
Variance					
sigma2_e	0.005***	0.005***	0.005***	0.005***	0.005**
	(37.99)	(37.98)	(37.87)	(37.60)	(37.73)
Controls	Yes	Yes	Yes	Yes	Yes

City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R2	0.146	0.159	0.000	0.008	0.082
N	2890	2890	2890	2890	2890

Notes: This table summarizes the spatial spillover effects of digital finance on industrial structure upgrading without control variables. Table 9 takes the SAR model as an example to investigate the causality of Dif and Isu under different spatial weighting matrices. According to the estimation results of Dif and Bread, industrial structure upgrading can be promoted mainly by digital finance. This effect is most significant under the adjacency matrix. Besides, inside the brackets in the table are the t-statistics, and *** means p-value <0.01, ** denotes p-value <0.05, * implies p-value <0.1.

4.4. Further heterogeneity analyses

Since economic development is a fundamental factor influencing financial development and industrial structure, the samples are divided into two groups, high and low, according to the GDP per capita. And then, this study runs separate regressions for further comparative analysis. Columns (1) and (3) of Table 10 reveal the estimation results. Comparing the coefficients of Dif, it can be seen that digital finance, in general, exerts a more significant influence on cities with higher economic levels (0.164 > 0.034). However, the coverage brings a more noticeable impact in economically backward areas (0.174 > 0.141). This evidence represents that expanding the coverage of digital finance in economically underdeveloped areas, such as rural areas, helps to achieve digital finance inclusiveness (see Table 10).

Table 10. Heterogeneity Analysis is Based on the Different Economic and Financial Levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Lower economic cities		Higher economic cities		Lower financial cities	
	Isu	Isu	Isu	Isu	Isu	Isu
Dif	0.034		0.164**		0.131*	
	(0.49)		(2.04)		(1.70)	
Bread		0.174*		0.141*		0.119*
		(1.95)		(1.82)		(1.70)
Constant	0.483	0.385	0.041	0.078	−0.033	0.077
	(1.27)	(1.05)	(0.06)	(0.11)	(-0.05)	(0.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.850	0.851	0.891	0.890	0.845	0.845

N	1440	1440	1450	1450	1440	1440

Note: Based on the level of economic development, the degree of financialization and the degree of income inequality, this paper divides all cities into high and low groups according to the median, respectively.

Furthermore, the penetration of digital finance is closely linked to traditional finance. We measure cities' financialization level based on the proportion of deposit and loan balances of financial institutions to annual GDP (Wu et al., 2022). Again, the samples are divided into high and low groups according to the median. In the comparison between columns (5) and (7) of Table 10, it's clear that the influence of digital finance is more substantial in cities with lower financialization levels. This indicates that digital finance can complement traditional finance and make up for the lack of traditional finance.

Many studies reveal that digital finance can alleviate income inequality (Luo and Li, 2022). By comparing the function of digital finance in cities with different earning disparities, this study can verify, to a certain extent, the inclusive nature of digital finance. The results in Table 11 signify that digital finance plays a more significant role in cities with small income disparities (i.e., small Theil index). In cities with severe income inequality, digital finance cannot exert a substantial effect on Isu. Therefore, this result cannot reflect the universality of digital finance. However, the coefficients of Dif in different subgroups indicate that digital finance does exert a heterogeneous effect on industrial structure. This proves that **Hypothesis 4** is valid.

Table 11. Heterogeneity Analysis is Based on Different Income Gaps.

	(1)	(2)	(3)
	Lower Theil index		Higher Theil index
	Isu	Isu	Isu
Dif	0.149**		0.034
	(2.40)		(0.51)
Bread		0.180**	
		(2.58)	
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R2	0.877	0.878	0.865
N	1840	1840	1890

Notes: The Theil index measures the degree of economic inequality. The larger the index, the greater the income gap in the city. The results reveal that digital finance exerts a more prominent influence in cities with smaller income gaps. The breadth of coverage in the sub-index is also greater in cities with relatively equal incomes. Besides, inside the brackets in the table are the t-statistics, and *** means p-value <0.01, ** denotes p-value <0.05, * implies p-value <0.1.

4.5. Additional robustness checks

We perform robustness tests by replacing proxy variables for the industrial structure upgrading and by using the systematic GMM (Generalized Method of Moments) estimation method (Wang and Wang, 2021) to further verify the accuracy of the benchmark findings.

4.5.1. Replacing the dependent variable

Based on the description of Isu_govern in Section 3.2.1., this study uses Isu_govern as an indicator of industrial structure upgrading through the lens of government to measure the government's attention allocation to different industries (Xu et al., 2022). From the regression result in Table 12, the government's attention to the tertiary industry increases significantly under the expansion of digital finance. Among the sub-indicators, the power of the depth of use of digital finance is particularly significant. This evidence indicates that digital finance still significantly contributes to industrial structure upgrading from the government level, which also proves the reliability of the benchmark results.

Table 12. Robustness test with alternative proxy variable and system GMM estimations.

	(1)	(2)	(3)	(4)
	Isu_govern	Isu_ govern	Isu_ govern	Isu_ govern
L.Isu				

Dif	0.183***			
	(2.63)			
Bread		0.064		
		(0.84)		
Depth			0.111***	
			(2.68)	
Digit				0.029*
				(1.74)
Constant	1.424***	1.665***	1.516***	1.652***
	(3.66)	(4.48)	(4.03)	(4.34)
AR (1) test				
AR (2) test				
Hansen test				
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

R2	0.641	0.639	0.641	0.640
N	2684	2684	2684	2684

Notes: Isu_govern in the table measures industrial structural upgrading in terms of government attention. L.Isu is the lag term of the index of industrial structural upgrading with one year lag, which measures dynamic effects. Columns (1)–(4) are the regression results after replacing the dependent variables. Column (5) presents the estimation results with the systematic GMM. AR (1) and AR (2) report the results of the Arellano-Bond test, proving that εit is not autocorrelated. Hansen's test is an over-identification test, proving that all instrumental variables are exogenous. This evidence shows that the systematic GMM estimation method is applicable. The benchmark findings pass the robustness test according to the coefficients of the indicators of digital finance. Industrial structure upgrading can be substantially boosted by digital finance.

4.5.2. Using an alternative estimation method

Since industrial structure upgrading tends to have strong path dependence (Song et al., 2021), i.e., the Isu in the current period may be influenced by previous Isu, thus creating an endogeneity problem. Therefore, this paper includes a lagged industrial structure upgrading index, Isui,t−1, to the independent variables and uses a systematic GMM method for dynamic panel estimation to mitigate the endogeneity problem. The dynamic panel model is specified as follows:(12)Isuit=φ0+φ1Isui,t−1+φ2Difit+φcXit+μi+δt+εitwhere the meaning of the variables is identical to that of Eq. (1).

Column (5) of Table 12 shows the regression results according to Eq. (12). Results of the AR (1) test and AR (2) test, and Hansen test indicates that the premise assumptions of the systematic GMM are valid and the model estimation results are reliable, which again proves that industrial structure upgrading can be substantially facilitated by digital finance.

5. Conclusion

This paper investigates the causality of digital finance and industrial structure upgrading using panel data for 289 prefecture-level cities in China from 2011 to 2020. And fixed effect model, spatial econometric model and mediating effect model are employed to empirically demonstrate the causality of digital finance (together with its sub-indicators) and industrial structure upgrading and to investigate the influence mechanism.

The empirical findings are as follows. (1) The benchmark regression shows that digital finance can effectively facilitate industrial structure upgrading in Chinese cities. Among the sub-indicators of digital finance, the effect of the breadth of coverage is the most pronounced. (2) The spatial econometric study results prove that digital finance development and industrial structure upgrading exhibit prominent spatial autocorrelation. Nevertheless, digital finance development in peripheral cities negatively influences local industrial structure upgrading, possibly due to digital finance's industrial agglomeration effect (or siphon effect). (3) The mediating effect analysis shows that digital finance can indirectly influence industrial structural upgrading by boosting urban innovation and entrepreneurship and adjusting the structure of household consumption expenditure. (4) Heterogeneity analysis reveals that the influence of digital finance is more significant in cities with more developed economies, less financialization and lower earning disparity. (5) The results of robustness tests support the above empirical findings.

According to the above analysis and the actual situation of China's economic development, policy recommendations are put forward: First, regions with relatively backward traditional financial development and undeveloped industrial patterns have a latecomer advantage. Local governments can facilitate the industrial structure upgrading of backward regions through digital financial development. Authorities should vigorously build digital financial infrastructure and accelerate the informatization of financial infrastructure. In addition, they should accelerate the facilitation of payment and credit systems and better play the positive significance of digital financial services. Second, the relationship between digital finance and the domestic economy also faces the problem of “moderate matching”, and the government and financial institutions should avoid the hollowing out of the industry caused by “excessive financialization”. Third, the financial industry regulators should speed up establishing a compliance system in digital finance and clarify the positioning of “financial services for the real economy”. Moreover, they should attach more importance to compliance issues and adopt risk-avoidance measures to avoid the outbreak of considerable risks in the digital finance sector, affecting the overall economic situation.

This study analyzes the influence of digital finance on industrial structure upgrading as comprehensively as possible within the existing data conditions and research methods. It complements the empirical evidence on this research question. However, the existing indicators of industrial structure upgrading are constructed relatively simply, considering only the proportion of output value of different industries, which cannot fully reflect the rationality and superiority of industrial structure. Future research can start by constructing indicators more representative of industrial structure optimization. Or analyze the determinants of the industrial structure under the context of the digital economy from multiple perspectives. In addition, with the updating and iteration of research methods, econometric models that better fit this research problem may emerge. Therefore, this question needs to be further studied in depth.