

# THE IMPACT OF DIGITAL ECONOMY ON INDUSTRIAL STRUCTURE UPGRADING: A STRATEGIC CONTEXT

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## Abstract

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The primary objective of this paper is to investigate the impact of the digital economy on the upgrading of industrial structures. Drawing upon existing research (Wang & Wei, 2024; Luo, 2024), this study integrates technological innovation, factor allocation efficiency, the digital economy, and industrial structure into a unified analytical framework to examine the underlying mechanisms. Based on data collected from 296 prefecture-level cities in China between 2015 and 2018, and employing both the two-way fixed effects model and the mediation effect model, an empirical analysis is conducted. The results indicate that the development of the digital economy has facilitated the transformation of industrial structures toward more advanced and rational configurations. This effect is partially mediated by technological innovation and enhanced factor allocation efficiency. The findings also reveal that the influence is more pronounced in China's central and Western regions as well as in large cities. Policy recommendations include increasing investment in digital infrastructure, accelerating the development of digital talent, promoting technological innovation and the application of digital technologies in enterprises, improving the efficiency of factor resource allocation by facilitating factor mobility, and enhancing digital economy development in central and Western regions to foster inclusive digital growth.

**Keywords:** Digital Economy, Industrial Structure, Resource Allocation

**Authors' individual contribution:** Conceptualization — C.W.; Methodology — X.Y.; Formal Analysis — X.Y.; Data Curation — X.Y.; Writing — Original Draft — X.Y.; Writing — Review & Editing — C.W.; Supervision — C.W.

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## 1. INTRODUCTION

The report of the Party's 20th National Congress (Ministry of Commerce of the People's Republic of China, 2022) emphasized the imperative to expedite the establishment of a novel development paradigm, with a focus on promoting high-quality development and constructing a modern industrial system.

The government work report further reiterated that vigorously advancing the construction of a modern industrial system and accelerating innovative productivity development are key tasks for 2024. A modern industrial system refers to an interconnected and mutually supportive framework that evolves among various industries during the process of modernization. Its primary

objective is to optimize and upgrade the industrial structure by transitioning towards technology-intensive and knowledge-based sectors, fostering intelligent growth in traditional industries, as well as nurturing strategic emerging industries. However, China has been grappling with issues such as homogenization in its industrial layout, overall manufacturing overcapacity, inadequate service industry capacity (Xu & Zhang, 2020; Luo, 2024), along with other structural contradictions within its industries. Additionally, it faces challenges stemming from diminishing demographic dividends and declining industrial competitiveness (Han & Li, 2022). Therefore, there is an urgent need to adjust the industrial structure and expedite industry integration in order to provide impetus for high-quality economic development.

On the contrary, with the rapid advancement of cutting-edge information technologies such as big data, artificial intelligence, and cloud computing, the share of the digital economy in the national economy has progressively escalated. Consequently, the digital economy has emerged as a pivotal impetus for a country's economic progress. The development of the digital economy has exerted a profound influence on various aspects, including production, exchange, distribution, and consumption patterns. This article is devoted to conducting in-depth research on the following research questions:

*RQ1: Does this impact extend to the industrial level by fostering resource flow towards high-value-added and technology-intensive sectors?*

*RQ2: Does it elevate the proportion of such industries and further facilitate industrial transformation and upgrading?*

The structure of this paper is as follows. Section 2 reviews the relevant literature. Section 3 analyses the methodology that has been used to conduct empirical research. Section 4 presents the results, highlighting key findings, and Section 5 discusses these findings in the context of existing research. Lastly, Section 6 offers practical recommendations for policymakers and provides further clarification regarding the theoretical contributions of the study, limitations, and recommendations for future studies.

## 2. LITERATURE REVIEW

### 2.1. Research on the transformation of industrial structure

The transformation of industrial structure reflects the process of reallocating production factors across different industries (Zhang et al., 2023). Existing studies commonly employ either single indicators or composite indicators to assess the extent of industrial structural transformation. Frequently used single indicators include employment share and value-added share (Wu & Guo, 2023). Composite indicators, such as industrial structure upgrading and industrial structure rationalization, are also widely adopted (Jia & Tao, 2023). Current research has identified that demand-side factors, such as income effects, investment structure, and external demand composition, can influence industrial structural transformation (Xu & Zhang, 2020; Herrendorf et al., 2021; Alder et al., 2022).

On the supply side, technological progress and capital deepening have also been found to exert significant impacts on such transformation (Acemoglu & Guerrieri, 2008; Xu & Wang, 2021). Furthermore, additional factors, including government policies (Ma & Huang, 2023) and income distribution (Guo et al., 2024), may also indirectly influence the process of industrial structural change.

### 2.2. Research on the digital economy

The digital economy is an economic paradigm in which data serves as the core resource, information platforms function as the primary carrier, and digital technologies act as the principal driving force, accompanied by the emergence of a variety of new business models (Chen et al., 2025). Much of the existing literature constructs indices to measure the development level of the digital economy based on two main dimensions: industrial digitalization and digital industrialization (Xia et al., 2024). Numerous studies have investigated the impacts of the digital economy across multiple domains, including economic efficiency, regional development, and industrial transformation (Liu & Chen, 2023; Song et al., 2023; Guo, 2023).

### 2.3. Research on the impact of the digital economy on industrial structure transformation

Existing literature has examined the impact of the digital economy on industrial structure transformation from the perspective of supply-side factors, such as technological innovation (Yu et al., 2024), capital deepening (Song et al., 2023), factor substitution (Wang & Yuan, 2018), and technology bias (Guo et al., 2020). Additionally, demand-side factors — such as consumption, investment, and exports — have also been explored in relation to this transformation (Liu, 2022; Liu & Li, 2023; Qi & Chu, 2021). Combined with previous studies, this paper integrates technological innovation, factor allocation efficiency, the digital economy, and industrial structure within a unified research framework. It aims to explore the mechanism through which the digital economy influences industrial structure from the perspectives of technological innovation and factor allocation.

### 2.4. Theoretical analysis

Firstly, the advancement of digital technology has enhanced individuals' capacity to collect and process data, enabling its application in production decision-making. This facilitates micro-entities such as enterprises to align their supply decisions with market demand, mitigating production risks while enhancing efficiency and yield. Consequently, micro-entities are incentivized to adopt more digital technologies and equipment in their production processes, transforming the decision-making of production factors and propelling a shift from labor-intensive to capital or technology-intensive modes of production. This paves the way for the realization of traditional manufacturing's transformation and upgrade towards high-end manufacturing. Secondly, the progress of digital technology has also bolstered information transmission efficiency by surpassing temporal and spatial limitations. As a result, it has

revolutionized trading methods by overcoming offline market constraints on time and space. Online market transactions have reduced information asymmetry while significantly improving exchange efficiency. Simultaneously, this pivotal moment has witnessed the emergence of new business models like the platform economy, sharing economy, and digital services related to online markets that disrupt traditional divisions of labor. Thirdly, with the development of online markets comes intensified competition within sellers' markets, leading to fairer pricing practices along with increased transparency for consumers. Consequently, consumers now possess higher expectations regarding product/service quality and diversity, which further stimulates diversification in product/service supply while fostering deeper divisions within production processes.

The aforementioned three aspects collectively indicate that the advancement of the digital economy will facilitate a transformation in the division of production. The division of production serves as the foundation for determining interrelationships among various industries within the industrial chain. Each industry within this chain is interconnected due to distinct divisions of labor, and any alterations in these divisions are bound to result in changes to the industrial structure. Emerging industries associated with digital technology attract greater investments, acquire more resources, experience accelerated growth rates, and consequently increase their proportion within the industrial structure, thereby driving a shift from low value-added and low technology-intensive forms towards high value-added and high technology-intensive forms, ultimately realizing an advanced industrial structure. Moreover, integrating traditional industries with digital technologies can also propel traditional sectors towards advanced levels. Simultaneously, advancements in digital technology enhance rationalization of the industrial structure by augmenting micro-entities' capacity to collect and process data efficiently, improving decision-making efficacy, promoting supply-demand alignment, and enhancing overall rationality within the industrial framework. The first hypothesis is, therefore, proposed:

*H1: The advancement and rationalization of the industrial structure are facilitated by the development of the digital economy, leading to the realization of industrial structural transformation and upgrading.*

Schumpeter (1934) posited that innovation constitutes a novel combination of production factors, encompassing five distinct forms: the introduction of new products, the application of new technologies, the opening of new markets, the utilization of new sources of supply, and the establishment of new organizational structures. He underscored the endogenous nature of innovation, its revolutionary impact, and the principle of creative destruction. The advancement of the digital economy facilitates technological innovation by alleviating financial constraints, enhancing the efficiency of talent allocation, prompting enterprises to reconfigure production factors, and encouraging the development of new products and expansion into new markets. A detailed analysis is provided as

follows. Firstly, the advancement of digital finance helps alleviate enterprise financing constraints, enabling them to allocate more funds towards areas such as product research and development for technological innovation. Simultaneously, enhanced information transmission efficiency reduces transaction costs (including search costs, information costs, bargaining costs, and supervision costs), thereby improving enterprise management efficiency and returns. This alleviates capital constraints on innovative investments by enterprises and consequently promotes technological innovation. Secondly, a digitally-driven economy based on advancements in information technology also aids in attracting innovative talent for research and development (R&D) capital while enhancing the allocation efficiency of innovation factors. As a result, it elevates the level of technological innovation achieved. Thirdly, improvements in digital data collection capabilities, along with processing techniques, enable enterprises to accurately grasp consumer demands. With the growth of digital technology and online markets comes an increased demand for digital products and services from consumers; this change in consumer demand compels enterprises to increase their expenditure on innovating digital offerings to meet market needs. The emergence of new products/services/models generates additional industries related to digital technology while increasing their overall proportion within industrial structures. The second hypothesis is, therefore, proposed:

*H2: The advancement of the digital economy facilitates industrial structural upgrading by fostering technological innovation.*

The digital economy can also enhance the efficiency of factor allocation within and between regions. The application of information technology not only facilitates the unrestricted movement of production factors such as labor and capital between different industries in the same region but also transcends regional limitations, eliminates trade barriers caused by systems and geographical distance, and expedites the flow of production factors across regions. From the perspective of dynamic capabilities theory, in the context of a rapidly evolving environment, enterprises must continuously reconfigure their resource portfolios to sustain competitive advantage through three core capabilities: opportunity and threat sensing (e.g., identifying emerging market trends), strategic resource reconfiguration (e.g., technological innovation or organizational restructuring), and learning and adaptive capacity (e.g., knowledge accumulation and operational process optimization). The integration of information technology and the seamless flow of production factors foster a conducive environment for enhancing these dynamic capabilities. In turn, the strengthening of enterprise-level dynamic capabilities contributes significantly to industrial structural upgrading. On the other hand, given the promising development prospects of the digital economy, enterprises associated with it tend to yield higher returns on marginal factor products, thereby attracting production factors to gravitate towards these advantageous industries and regions. Consequently, resource allocation efficiency between

different regions, as well as within the same region, will be enhanced. With abundant resources at their disposal, advantageous industries linked to the digital economy will experience rapid growth, fostering an increase in high-value-added and high-tech intensive sectors while driving industrial structural upgrading. The improvement in inter-industry resource allocation efficiency is also conducive to a more rational industrial structure. The third hypothesis is, therefore, proposed:

*H3: The advancement of the digital economy facilitates the enhancement of the industrial structure through optimizing resource allocation efficiency.*

$$IS_{ct} = \alpha_0 + \alpha_1 Dig_{ct} + \sum_{j=2}^n \alpha_j CV_{ct} + \mu_c + v_t + \varepsilon_{ct} \tag{1}$$

In the given context, where  $c$  represents a specific city and  $t$  signifies a particular point in time, this study quantifies the degree of industrial structure upgrading in city  $c$  at time  $t$  ( $IS_{ct}$ ), encompassing two indices:  $Ais$  for structural upgrading and  $Ris$  for rationalization.  $Dig_{ct}$  represents the level of digital economic development achieved by city  $c$  at time  $t$ . Moreover,  $\alpha_1$  is an influence coefficient reflecting the impact of a city's digital economy on its industrial structure upgrades. If  $\alpha_1 > 0$ , the advancement of a city's digital economy promotes improvements in its industrial structure. Additionally,  $CV_{ct}$  are several control variables for city  $c$  at time  $t$ , including levels of human capital ( $Hc$ ), educational investments

### 3. RESEARCH METHODOLOGY

#### 3.1. Model specification

##### 3.1.1. Benchmark model setting

From theoretical and empirical perspectives, industrial structure upgrading is influenced by numerous factors, and their relationships can be constructed through an economic model. The benchmark regression model is formulated as follows:

( $Edu$ ), regional economic growth ( $Pgdp$ ), financial developments ( $Finan$ ), information accessibility ( $Info$ ), governmental interventions ( $Budg$ ), and investment level of science and technology ( $Scien$ ). And  $\mu_c$  and  $v_t$  represent the city fixed effect and time fixed effect, respectively.  $\varepsilon_{ct}$  is a random error term.

##### 3.1.2. Intermediate effect model

The mechanism testing part of this paper mainly adopts the mediation effect model, including the following three regression equations:

$$IS_{ct} = \beta_0 + \beta_1 Dig_{ct} + \sum_{j=2}^n \beta_j CV_{ct} + \mu_c + v_t + \varepsilon_{ct} \tag{2}$$

$$Med_{ct} = \gamma_0 + \gamma_1 Dig_{ct} + \sum_{j=2}^n \gamma_j CV_{ct} + \mu_c + v_t + \delta_{ct} \tag{3}$$

$$IS_{ct} = \omega_0 + \omega_1 Dig_{ct} + \omega_2 Med_{ct} + \sum_{j=3}^n \omega_j CV_{ct} + \mu_c + v_t + \sigma_{ct} \tag{4}$$

$Med_{ct}$  is the intermediate variable, including the per capita number of invention patent applications ( $Pate$ ), urban total factor productivity ( $Tfp$ ), urban resource allocation efficiency ( $Allo$ ), and technological progress rate ( $Tech$ ). The coefficient of the intermediate effect model needs validation. If all three variables are statistically significant, it indicates a substantial intermediary effect, where the level of urban digital economy development ( $Dig_{ct}$ ) influences the degree of upgrading in urban industrial structure ( $IS_{ct}$ ) through these intermediary variables ( $Med_{ct}$ ). Based on the significance level of  $\omega_2$ , we can determine whether the mediating effect is complete or partial.

#### 3.2. Variable introduction

##### 3.2.1. Dependent variable: The degree of upgrading in urban industrial structure

The advancement of industrial structure is assessed through two indicators, the upgrading ( $Ais$ ) and

rationalization ( $Ris$ ) of industrial structure. In previous studies conducted by Xu and Jiang (2015), the structural upgrading index of three types of industries has been employed to reflect the extent of improvement in industrial structure. This study also adopts this methodology, with the calculation equation:

$$Ais_{ct} = \sum_{i=1}^3 Pr_{cit} * i \tag{5}$$

where,  $Pr_{cit}$  represents the proportion of the output value of industry  $i$  in the gross regional product of city  $c$  at time  $t$ . The higher the value of  $Ais_{ct}$ , the more advanced the development of the industrial structure. The equation for calculating the rationalization of industrial structure is as follows:

$$Ris_{ct} = \sum_{i=1}^3 Pr_{cit} * \ln \left( \frac{Pr_{cit}}{l_{cit}} \right) \tag{6}$$

where,  $l_{cit}$  represents the ratio of employment in industry  $i$  to total employment in city  $c$  at time  $t$ . If  $l_{cit} = 0$ , it indicates that the output value structure aligns with the employment structure, reflecting a high degree of rationalization. The further the value deviates from 0, the more irrational the industrial structure becomes.

### 3.2.2. Independent variable: Level of development in the digital economy

This paper employs the level of Internet development as a metric to gauge the extent of advancement in the digital economy within each city. The Internet serves as the primary conduit for digital economic activities, and a higher number of internet users within a city signifies a stronger foundation for growth in the digital economy, with profound implications on production, exchange, and distribution modes. Therefore, we utilize the count of broadband access users as an indicator (*Inte*) (logarithmically transformed) to measure the level of development in the digital economy. Additionally, existing literature often utilizes Tencent Research Institute's Digital China Index (*Di*) (logarithmically transformed). The index is derived from data collected across 351 cities through apps such as WeChat, Meituan, Didi, and Pinduoduo. It is calculated based on the weighted average of four sub-indices: digital industry, digital government, digital life, and digital culture. As a result, it provides a more comprehensive reflection of the level of development in each city's digital economy. In order to effectively test robustness in our study designations, this index is employed as an alternative variable representing the level of Internet development.

### 3.2.3. Intermediate variables

This paper initially employs the ratio of total science and technology expenditure to total patent applications as a measure of the efficiency in science and technology output for each city, thereby reflecting the level of innovation in each city's patents. Furthermore, data envelopment analysis is utilized to calculate the total factor productivity (*Tfp*) for each city, which is then decomposed into technical efficiency (*Tech*) and allocative efficiency (*Allo*). Technical efficiency serves as a proxy variable for urban innovation level, while allocative efficiency represents resource allocation level. The calculation of urban *Tfp* involves determining capital stock using Zhang et al.'s (2004) method as a reference and calculating income based on 2000 figures. Additionally, when considering gross regional product, the gross domestic product (GDP) deflator for each prefecture-level city is adjusted to reflect the base period of 2000. Labor force data is measured by averaging employee numbers on active duty.

### 3.2.4. Control variables

According to the research conducted by Jiang et al. (2018), education, particularly higher education, will exert a significant influence on the transformation of industrial structure. In this study, we utilize the indicator of students enrolled in ordinary colleges and universities per 10,000 individuals as

a measure of human capital level in a city (*Hc*) (logarithmically transformed). Additionally, total educational expenditure is selected as a metric to gauge the investment level in education for each city (*Edu*) (logarithmically transformed). Furthermore, based on the findings from Han and Li's (2022) research, it is evident that regional economic development level (*Pgdp*) (logarithmically transformed), financial development level (*Finan*), and informatization level (*Info*) (logarithmically transformed) all have an impact on industrial structure. Therefore, we choose to employ per capita GDP of each city, the ratio of financial institutions' renminbi (RMB) deposits and loans balance to end-of-year GDP, and number of mobile phone users at year-end as indicators reflecting economic status, financial development levels, and information technology levels, respectively. Moreover, this paper also incorporates control variables such as the ratio of local general public budget expenditure to regional gross domestic product and the ratio of total science and technology expenditure to local general public budget expenditure for measuring the degree of local government intervention (*Budg*) and science and technology investment in each city (*Scien*) (logarithmically transformed).

### 3.3. Data sources and descriptive statistics

The Digital China Index was initially derived from the Tencent Internet + Index, which was released in 2015 to reflect the development of the digital economy across various cities in 2014. However, there are significant disparities in statistical indicators between this dataset and subsequent years' data. Moreover, since 2020, detailed digital economy indexes for individual cities have not been published by Tencent Research Institute. Consequently, the Digital China Index can only utilize a sample from 2015 to 2018. Although we primarily employ this indicator in the robustness test section, we have standardized all empirical tests' sample intervals to align with this time period selection criterion for maintaining consistency with our robustness testing approach. Consistent with prior literature (Han & Li, 2022; Liao et al., 2024), we have chosen the period from 2015 to 2018 as our sample interval.

The indicators in this paper primarily originate from the China City Statistical Yearbook and Provincial Statistical Yearbook, with any missing data being supplemented through a search of provincial and municipal government bulletins. Due to significant data gaps in certain cities, this study selected 296 prefecture-level cities as research samples. Data on the number of city patent applications were obtained from the online patent search system of the China Intellectual Property Office. The instrumental variable used for determining the minimum distance between each city's centroid and the "eight vertical and eight horizontal" cable backbone node city is sourced from the Rstata Academy database.

In order to mitigate the impact of outliers, a 1% reduction is applied to the main variables. After excluding samples where the industrial structure rationalization (*Ris*) equals zero, descriptive statistical results are presented in Table 1. Examining the statistical outcomes of the dependent variables reveals their small standard deviations and relative data stability. Notably, both the Internet

development index and digital economy index surpass the standard deviation of the dependent variable, indicating significant disparities in digital economy development among cities and highlighting regional digital divides. Analyzing standard deviations of control and intermediary variables demonstrates that all variables, except for financial

development level and science and technology input, have a standard deviation below 1%. This suggests that fluctuations in financial development and science and technology input across different cities are greater than those observed in other aspects, aligning with empirical evidence.

**Table 1.** Descriptive statistics

Variable	Size	Mean	Std. dev.	Min	Max
<i>Ais</i>	1135	2.430	0.130	1.810	2.730
<i>Ris</i>	1135	0.170	0.180	-0.100	0.810
<i>Inte</i>	1130	4.320	0.790	2.830	5.770
<i>Di</i>	1135	-0.720	1.150	-2.860	3.110
<i>Info</i>	1132	5.830	0.690	4.550	7.200
<i>Pgdp</i>	1118	10.99	0.520	9.850	12.04
<i>Finan</i>	1135	3.380	1.500	0.720	8.390
<i>Hc</i>	1092	4.700	0.980	3.040	6.730
<i>Budg</i>	1135	0.190	0.0800	0.0800	0.360
<i>Scien</i>	1135	9.560	1.830	5.510	14.35
<i>Edu</i>	1135	13.23	0.730	11.29	15.49
<i>Pate</i>	1119	0.100	0.0800	0	0.620
<i>Tfp</i>	908	1	0.0400	0.770	1.440
<i>Allo</i>	908	1	0.0400	0.790	1.340
<i>Tech</i>	908	1	0.0200	0.880	1.070

### 3.4. Alternative method

This study could also conduct empirical tests using more detailed county-level data. However, due to the numerous missing indicators in the county-level statistical yearbooks, it is quite challenging to collate and supplement this level of data. Therefore, this paper did not employ data at this level for the research.

## 4. RESULTS

### 4.1. Basic regression analysis

We employed Eq. (1) by substituting the number of Internet broadband access users in each region, the index *Ais* for upgrading industrial structure, and various control variables. The regression analysis was conducted using random effect (RE) and fixed

effect (FE) models with robust standard error estimation. The results are presented in columns 1 and 2 of Table 2. After replacing *Ais* with *Ris* for rationalizing industrial structure, the regression outcomes were displayed in columns 3 and 4 of Table 2. Based on the Sargan-Hansen test results, we found significant evidence to reject RE and thus adopted FE model instead. From the two columns presenting FE estimates, it can be observed that after controlling for individual-specific urban effects and time-fixed effects at a significance level of 10%, a 1% increase in Internet users leads to a rise in the degree of upgrading industrial structure by 0.017%, while simultaneously reducing irrationality in industrial structure by 0.0335%. This finding suggests that digital economy development holds substantial potential for promoting upgrades in industrial structure, thereby confirming *H1*.

**Table 2.** Basic regression

Variables	(1)	(2)	(3)	(4)
	<i>Ais</i> (RE)	<i>Ais</i> (FE)	<i>Ris</i> (RE)	<i>Ris</i> (FE)
<i>Inte</i>	0.0425*** (5.33)	0.0170* (1.81)	-0.0125 (-0.85)	-0.0335* (-1.82)
<i>Info</i>	0.0012 (0.10)	0.0048 (0.31)	0.0000 (0.00)	0.0581* (1.73)
<i>Pgdp</i>	0.0289* (2.37)	-0.0204 (-1.17)	-0.1042*** (-4.62)	-0.0522 (-1.53)
<i>Finan</i>	0.0267*** (5.12)	0.0150*** (3.14)	-0.0208*** (-4.00)	-0.0185** (-2.35)
<i>Hc</i>	0.0231*** (3.34)	0.0045 (0.41)	-0.0117 (-1.02)	-0.0006 (-0.03)
<i>Budg</i>	0.0574 (0.99)	0.0705 (1.15)	0.2948*** (2.83)	0.3205** (2.49)
<i>Scien</i>	-0.0037 (-1.43)	-0.0034 (-1.12)	-0.0012 (-0.22)	-0.0017 (-0.26)
<i>Edu</i>	0.0156 (1.64)	0.0019 (0.16)	0.0456** (2.34)	-0.0093 (-0.31)
Sargan-Hansen statistic	46.711*** 0.0000		34.931*** 0.0000	
Year		Yes		Yes
City		Yes		Yes
_cons	1.5370*** (10.38)	2.4516*** (9.10)	0.8461*** (3.41)	0.6854 (1.42)
N	1074	1074	1074	1074
R <sup>2</sup>	0.2976	0.3933	0.0336	0.0530

Note: The numbers in brackets are t-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

## 4.2. Robust analysis

### 4.2.1. Dependent variable replacement

The existing literature commonly utilizes the Digital China Index, published by Tencent Research Institute, as a metric to assess the level of digital economy development in different cities (Han & Li, 2022; Liao et al., 2024). Following this established approach, we substitute this index into Eq. (1), and present the regression results in columns 1 and 2 of Table 3. It is evident that at a significance level of 1%, each incremental percentage point increase in the Digital China Index corresponds to a rise of 0.0258% in levels of industrial structure upgrading. Furthermore, at a significance level of 10%, the Digital China Index significantly mitigates irrationalities within the industrial structure, with every additional percentage point resulting in a decrease of 0.0336%. Overall, an elevation in the Digital China Index effectively facilitates advanced-level development of industrial structures while simultaneously promoting their rationalization.

### 4.2.2. Sample transformation

Considering that municipalities directly under the Central Government possess greater advantages in resource acquisition compared to other cities, as well as a significant gap in information infrastructure construction and digital economy development, such as Internet transactions, this study excludes the samples of Beijing, Shanghai, Tianjin, and Chongqing municipalities. Regression analysis is then conducted on Eq. (1), with the results presented in columns 3 and 4 of Table 3. It can be observed that even after excluding these priority development samples, the level of digital economy represented by the Internet remains at approximately 10%, which effectively promotes industrial upgrading and prevents industry from deviating from rationalization. These findings

demonstrate certain robustness in relation to the baseline regression results.

### 4.2.3. Independent variables replacement

In order to mitigate the impact of selection bias in independent variable choice on regression results, we adopt the approach employed in previous studies (Yu et al., 2024) and utilize the ratio between tertiary industry output value and secondary industry output value as an indicator of industrial structure upgrading (*Ais2*). Based on the research conducted by Han et al. (2017) and Luo (2024), we utilize the equation

$$Ris2_{ct} = \sum_{i=1}^3 Pr_{cit} * \left| \frac{Pr_{cit}}{l_{cit} - 1} \right| \quad (7)$$

to quantitatively assess the degree of rationalization in industrial structure. By substituting these two indicators into Eq. (1) and conducting regression analysis, the results are presented in columns 5 and 6 of Table 3. The findings reveal that, with a significance level of 5%, a 1% increase in Internet access users leads to a corresponding increase of 0.0699% in the level of industrial structure. Furthermore, it is observed that a 1% rise in Internet access users not only enhances industrial structure upgrading by 0.0699%, but also reduces inappropriate allocation within the industrial structure by 1.8898%. Importantly, altering any variables or samples does not significantly impact the regression results presented in Table 2, thus confirming their robustness and reliability. Another noteworthy discovery is that, based on the regression coefficients for industrial structure upgrading and rationalization derived from Tables 2 and 3, respectively, it can be concluded that the digital economy plays a more substantial role as an agent for correcting imbalances within industrial structures than as a catalyst for promoting their overall advancement.

Table 3. Robustness test

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable replacement		Sample transformation		Independent variables replacement	
	<i>Ais</i>	<i>Ris</i>	<i>Ais</i>	<i>Ris</i>	<i>Ais2</i>	<i>Ris2</i>
<i>Di</i>	0.0258*** (2.91)	-0.0336* (-1.65)				
<i>Inte</i>			0.0169* (1.78)	-0.0334* (-1.80)	0.0699** (2.00)	-1.8898** (-2.06)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
_cons	2.6032*** (9.92)	0.3947 (0.79)	2.4502*** (8.97)	0.6774 (1.38)	1.4015 (0.98)	10.2568 (0.47)
N	1075	1075	1060	1060	904	1074
R <sup>2</sup>	0.3914	0.0486	0.3932	0.0532	0.3424	0.0153

Note: The numbers in brackets are t-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

## 4.3. Heterogeneity test

Given China's expansive territory, there exists a digital divide among its regions and a noticeable imbalance in economic development. Consequently, it is imperative to conduct a regional analysis on the impact of industrial structure within the digital economy. After stratifying the samples into

the Eastern region and the central and Western regions, we performed a sub-sample test using Eq.(1), with results presented in Table 4. From columns 1 and 2, it can be observed that the number of Internet access users does not significantly influence industrial structure upgrading or rationalization. However, for the central and Western regions mentioned in columns 3 and 4,

there is a significant effect of Internet development level on industrial structure variables. In this region characterized by advancements in the digital economy through Internet development, both an increased degree of advanced industrial structure at a significance level of 10% and a reduced degree of unreasonable industrial structure have been

notably impacted. With every 1% increase in Internet development level, there is an associated increase of 0.0198% in the advanced degree of industrial structure for these central and Western regions, while simultaneously reducing unreasonable degrees by 0.0384%.

Table 4. Heterogeneity test I

Variables	(1)	(2)	(3)	(4)
	East area		Midwest area	
	Ais	Ris	Ais	Ris
Inte	0.0065 (0.60)	-0.0401 (-1.42)	0.0198* (1.69)	-0.0384* (-1.73)
Control variable	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
_cons	1.8985*** (3.54)	0.1587 (0.14)	2.6310*** (8.53)	0.8051 (1.59)
N	384	384	690	690
R <sup>2</sup>	0.3267	0.0520	0.4500	0.0760

Note: The numbers in brackets are t-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

Considering the potential impact of population agglomeration effect or industrial agglomeration effect, it is necessary to classify cities based on their population size in order to capture the variations in the influence of the digital economy on the industrial structure. Accordingly, small cities are defined as those with an average annual population of less than one million, medium-sized cities have an average annual population between one million and five million, while large cities have an average annual population exceeding five million. Subsequently, a subsample regression analysis is

conducted using Eq. (1). The findings are presented in Table 5. In small and medium-sized cities, there is no significant evidence that the level of digital economy represented by the Internet has promoted the transformation and upgrading of the industrial structure. However, in large cities, a clear positive effect can be observed. Specifically, at a significance level of 5%, for every 1% increase in digital economy development, there will be a corresponding increase of 0.0173% in the industrial structure upgrading degree and a decrease of 0.0423% in the irrationality degree.

Table 5. Heterogeneity test II

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Small-sized		Medium-sized		Large-sized	
	Ris	Ais	Ris	Ais	Ris	Ais
Inte	-0.0269 (-0.73)	-0.0108 (-0.65)	-0.0188 (-0.71)	0.0178 (1.28)	-0.0423** (-2.12)	0.0173** (2.42)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-5.8882** (-2.48)	-0.3828 (-0.18)	0.6482 (1.16)	2.5369*** (8.45)	0.8607 (0.58)	2.3206*** (5.52)
N	45	45	649	649	380	380
R <sup>2</sup>	0.6520	0.5678	0.0510	0.4088	0.1105	0.4190

Note: The numbers in brackets are t-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

#### 4.4. Endogeneity

In this paper, the dual fixed effect model effectively addresses the issue of missing variables caused by urban individual heterogeneity and temporal heterogeneity; however, it does not resolve the problem of endogeneity resulting from measurement errors and reverse causality. Moreover, while this study employs the number of Internet access and the Digital China Index to gauge the level of digital economy development in each city, potential measurement errors may introduce bias into our estimation results. Additionally, industrial structural upgrades can potentially lead to increased data generation and collection in production, exchange, and distribution processes, thereby exerting pressure on digital economy development. Consequently, a significant reverse causality exists

between industrial structure and digital economy development. To address these issues arising from measurement error and reverse causation, we employ instrumental variable methods in this paper.

Firstly, based on the study conducted by Han and Li (2022), we employ the number of Internet user accesses in other cities within the same province as an instrumental variable (*Inte\_iv*) to estimate the number of Internet user accesses in each sample city. Given the high degree of correlation in geographical location, historical culture, and economic development among prefecture-level cities within the same province, the relevance condition for the instrumental variable — namely, its association with the endogenous variable — is reasonably satisfied. Furthermore, the influence of digital economic development in other cities within the province on the industrial

structure transformation and upgrading of a given region is relatively limited, thereby satisfying, to a considerable extent, the exogeneity assumption required for a valid instrumental variable. After conducting a two-stage least squares (2SLS) regression analysis, we present the results in Table 6. Columns 1 and 3 display the regression outcomes of the first stage using *Ais* and *Ris* as dependent variables, respectively, with Internet access serving as an independent variable. Columns 2 and 4 present the results of the second stage estimation. The statistical test data analysis reveals that in column 2, the Kleibergen-Paap Wald rk F-statistic is 26.1324, exceeding the critical value of the Stock-Yogo weak instrument test at a significance level of 10% which is set at 16.38; thus passing this test for weak instruments. Similarly, in column 4, with an rk F-statistic value of 26.2725, it also surpasses this critical value at a significance level below 10%. This indicates a strong correlation between instrumental variables and endogenous explanatory variables, suggesting that substantial bias will not be introduced through employing the 2SLS estimation method. Furthermore, *idstat* represents statistical results from unidentifiable tests using Kleibergen-Paap Wald rk approach; its p-value (*idstatp*) is reported as 0.0002 in column 2, indicating rejection of the null hypothesis regarding insufficient identification of instrumental variables at a significance level below or equal to 1%, which holds true for column 4.

The first-stage results in Table 6 demonstrate a significant positive effect of the instrumental variable (*Inte\_iv*) on Internet access at the 1% level, indicating its substantial influence on the core explanatory variable. The second-stage results reveal that Internet access significantly promotes industrial structure upgrading and effectively curbs irrational development at the 10% significance level. These findings highlight that even after addressing endogeneity concerns, Internet access continues to play a crucial role in facilitating the transformation and upgrading of the industrial structure.

Secondly, based on the research conducted by Zhang et al. (2023), we utilize the spherical distance between the centroid of each city and the “eight vertical and eight horizontal” cable backbone network node cities as an instrumental variable to determine the Digital China Index for each city. Regions that historically served as potential nodes for optical cable backbone networks are more likely to possess the necessary conditions for broadband

infrastructure deployment. Consequently, cities located in closer proximity to such node cities tend to exhibit stronger development in their digital economies. Given that, this geographical distance constitutes historical data, and it inherently possesses exogeneity. However, since this distance variable represents cross-sectional data, it is not suitable for panel data analysis. Therefore, drawing from Nunn et al.’s (2014) study along with Liu and Li’s (2023) work, we multiply the average number of Internet user access in other cities within the province where the sample city is located by the distance between that sample city and the backbone cities. This approach enables us to construct a tool variable known as *Di\_iv*. Subsequently, we employ the 2SLS method for regression analysis and present our findings in Table 7.

The regression results of the first stage, with *Ais* and *Ris* as dependent variables and the Digital China Index as an independent variable for 2SLS, are presented in columns 1 and 3 of Table 7, respectively. The regression results of the second stage are listed in columns 2 and 4. In column 2, the rk F-statistic is 18.59, which exceeds the critical value of 16.38 at a significance level of 10%, indicating successful passing of the weak instrumental variable test. Similarly, in column 4, the rk F-statistic also satisfies the criteria for passing the weak instrumental variable test. Furthermore, the p-value of *idstat* in column 2 is 0.0002, indicating that it successfully passes the instrumental variable unidentifiable test at the 1% significance level. The same applies to column 4.

According to the results of the initial stage presented in Table 7, at a significance level of 1%, there is a positive correlation between the size of the instrumental variable (*Di\_iv*) and its impact on enhancing the Digital China Index. The findings from the subsequent phase demonstrate that the development level of the digital economy, as measured by the Digital China Index, significantly facilitates industrial structure upgrading. Moreover, it is observed that industrial structure upgrading has a more substantial and significant promotion effect compared to industrial structure rationalization. Even after addressing endogeneity issues, it remains evident that the Digital China Index continues to significantly promote transformation and upgrading within industrial structures.

Table 6. Endogeneity test I

Variables	(1)	(2)	(3)	(4)
	<i>Inte</i>	<i>Ais</i>	<i>Inte</i>	<i>Ris</i>
<i>Inte_iv</i>	0.6383*** (5.11)		0.6420*** (5.13)	
<i>Inte</i>		0.0002* (1.71)		-0.0004* (-1.67)
Control variable	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
N	651	651	651	651
R <sup>2</sup>		0.3853		0.0530
rk F		26.1324		26.2725
<i>idstat</i>		14.3196		14.1189
<i>idstatp</i>		0.0002		0.0002

Note: The numbers in brackets are t-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

Table 7. Endogeneity test II

Variables	(1)	(2)	(3)	(4)
	<i>Di</i>	<i>Ais</i>	<i>Di</i>	<i>Ris</i>
<i>Di_iv</i>	0.0989*** (4.31)		0.0989*** (4.31)	
<i>Di</i>		0.2071*** (2.79)		-0.1982* (-1.77)
Control variable	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
N	802	802	802	802
R <sup>2</sup>		0.0664		-0.0503
rk F		18.5935		18.5935
<i>Idstat</i>		20.1515		20.1515
<i>idstatp</i>		0.0000		0.0000

Note: The numbers in brackets are t-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

#### 4.5. Mechanism test

From a theoretical perspective, the digital economy will facilitate the upgrading of the industrial structure by enhancing urban innovation and resource allocation efficiency. In this regard, we employ an intermediate effect model to examine this mediating mechanism. The first step in the mediation effect model (Eq. (2)) is identical to Eq. (1)) has been validated in our baseline regression analysis. Subsequently, we substitute the intermediate variable (*Pate*), dependent variable, and independent variable into Eq. (3) and 4 for regression analysis, yielding results as presented in Table 8. Column 1 demonstrates that the level of digital economy represented by the Internet significantly enhances a city's scientific and technological innovation capability at a significance

level of 10%. Column 2 reveals that even after incorporating the intermediary variable, the Internet-based measure of digital economy still significantly promotes advanced development of industrial structure; however, it should be noted that the coefficient before the intermediary variable is not statistically significant, indicating complete mediation effects are observed. Similarly, column 3 indicates that at a significance level of 10%, urban digital economy development inhibits irrationality within its industrial structure; moreover, once again highlighting insignificance for coefficients preceding intermediary variables — thus confirming complete mediation effects. Based on Table 8 findings, it can be concluded that urban digital economy development fosters industrial structural upgrading through enhanced innovation capabilities — a result consistent with H2.

Table 8. Intermediate test I

Variables	(1)	(2)	(3)
	<i>Pate</i>	<i>Ais</i>	<i>Ris</i>
<i>Inte</i>	0.0164* (1.74)	0.0173* (1.81)	-0.0323* (-1.74)
<i>Pate</i>		0.0089 (0.22)	-0.0592 (-0.86)
Control variable	Yes	Yes	Yes
Year	Yes	Yes	Yes
City	Yes	Yes	Yes
_cons	0.8183*** (3.22)	2.4324*** (8.98)	0.7519 (1.51)
N	1058	1058	1058
R <sup>2</sup>	0.3131	0.3941	0.0555

Note: The numbers in brackets are t-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

In order to further validate this mechanism, we employ urban total factor productivity as an indicator of urban innovation level and utilize the Digital China Index to represent the developmental stage of the digital economy in each city. Subsequently, we examine the mediating effect as presented in Table 9. From column 1, it is evident that the advancement of the digital economy significantly promotes urban total factor productivity at a significance level of 1%. Upon incorporating total factor productivity as an intermediary variable into the regression equation with *Ais* and *Ris* serving as dependent variables, the regression outcomes are displayed in columns 2 and 3. It can be observed that for every 1% increase in the Digital China Index, there is a substantial rise of 0.0286% in the industrial structure upgrading degree and a significant decrease of 0.0319% in the irrationality degree, both

indicating a complete mediating effect. Building upon Table 8, it further confirms that urban digital economic development fosters industrial structure upgrading by enhancing urban innovation levels.

In order to elucidate the specific sources of this mechanism, we decompose *Tfp* into two components: technology progress rate (*Tech*) and resource allocation efficiency (*Allo*), which are then substituted into the intermediary effect model for empirical testing. The corresponding results are presented in columns 4 to 7 of Table 9. As depicted in column 4, a 1% increase in the Digital China Index leads to a significant 0.0176% enhancement in resource allocation efficiency at the 10% level. When considering the outcomes from columns 5 and 6, it can be inferred that the advancement of the urban digital economy facilitates an upgrade in the urban industrial structure by ameliorating resource allocation efficiency. Furthermore, column 7 reveals

that there is no substantial promotion of urban technological progress resulting from digital economy development. Based on the findings derived from Table 9, we conclude that the urban digital economy primarily enhances urban total

factor productivity through improved resource allocation efficiency, thereby further promoting an upgrade in urban industrial structure — a confirmation of our theoretical *H3*.

**Table 9.** Intermediate test II

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	<i>Tfp</i>	<i>Ais</i>	<i>Ris</i>	<i>Allo</i>	<i>Ais</i>	<i>Ris</i>	<i>Tech</i>
<i>Di</i>	0.0151* (1.81)	0.0286*** (2.99)	-0.0319* (-1.72)	0.0176* (1.86)	0.0290*** (3.04)	-0.0316* (-1.71)	-0.0017 (-0.68)
<i>Tfp</i>		0.0012 (0.02)	0.0600 (1.57)				
<i>Allo</i>					-0.0203 (-0.49)	0.0347 (0.77)	
Control variable	Yes						
Year	Yes						
City	Yes						
_cons	1.1972*** (6.41)	2.8072*** (9.47)	0.4593 (0.86)	1.1891*** (5.58)	2.8327*** (9.63)	0.4898 (0.93)	1.0105*** (17.10)
N	862	862	862	862	862	862	862
R <sup>2</sup>	0.0298	0.4274	0.0465	0.1799	0.4277	0.0460	0.8111

Note: The numbers in brackets are *t*-values, \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels respectively.

## 5. DISCUSSION

Previous literature has primarily examined the impact of the digital economy on industrial structure upgrading from various perspectives, including residents' consumption and urban R&D innovation (Han & Li, 2022), intra-industry labor productivity (Liao et al., 2024), market demand and urbanization effects (Liu & Li, 2023), service sector efficiency (Liu et al., 2023), new infrastructure (Guo et al., 2020), technological progress disparities (Bai et al., 2021), regional innovation and entrepreneurial vitality (Li et al., 2021), and human capital combined with technological innovation (Liu & Chen, 2021). In contrast, this study investigates this issue through the lens of total factor productivity and resource allocation efficiency, thereby enriching the existing theoretical framework by exploring the underlying mechanisms and pathways.

In terms of empirical research, first, this study distinguishes itself from prior literature that predominantly employs single indicators — such as the number of patent applications or approvals, science and technology expenditures, and the number of scientific and technological personnel — to measure the level of urban technological innovation. Instead, this paper utilizes the total factor productivity of each city as a comprehensive indicator, which effectively addresses the limitations associated with individual metrics. Second, this study further decomposes total factor productivity into technical efficiency and factor allocation efficiency, and separately examines the mediating mechanisms of these two components, thereby addressing the gap in existing literature that primarily assesses factor allocation efficiency based on the degree of market integration. Thirdly, while current studies often rely on the product of the number of historical postal outlets in each city and the number of Internet users nationwide in the previous year as an instrumental variable for the digital economy, this paper adopts an alternative approach by employing the distance from each city center to the backbone optical cable city, along with the number of Internet broadband accesses in other cities within the same province, thereby enriching the empirical analysis of this topic.

## 6. CONCLUSION

This paper examines the impact of the digital economy on the upgrading of industrial structure from the perspectives of technological innovation and factor allocation efficiency. Empirical testing is conducted using a fixed effect model and an intermediary effect model based on data from 296 prefecture-level cities between 2015 and 2018. The results demonstrate that the development of the digital economy promotes urban industrial structure to reach a higher level and become more rational, which is supported by empirical findings from sub-sample data as well as after replacing key variables. Furthermore, even after addressing endogeneity issues, this conclusion remains valid. Mechanism analysis reveals that the development of the digital economy facilitates factor flow, enhances urban resource allocation efficiency, increases total factor productivity in cities, and subsequently drives the transformation and upgrading of the industrial structure. Heterogeneity analysis indicates that central and Western regions in China are significantly influenced by the digital economy in terms of their industrial structure improvement compared to large cities.

Therefore, this paper proposes the following policy recommendations:

Firstly, enhance support for market participants in the digital economy and fully leverage the developmental impact of the digital economy on industrial structure upgrading. By means of tax incentives, policy subsidies, interest rate concessions, and other measures, bolster assistance to small and medium-sized enterprises engaged in the digital economy while reducing entry barriers for emerging forms of the digital economy. Support the development and expansion of digital enterprises, steer the growth of industry clusters within the digital economy sector, and establish internationally competitive digital industry clusters.

Secondly, it is imperative to enhance the development of digital infrastructure, expedite the training of digital talents, and foster a culture that promotes technological innovation and application within enterprises operating in the digital economy. The findings of this study

indicate that the current progress of China's urban digital economy has not significantly bolstered the efficiency of urban technological advancement. Consequently, there is a pressing need to comprehensively encourage technological advancements and promote digital economy enterprises to augment their supportive role in enhancing urban technological progress.

Thirdly, it is crucial to streamline factor flows by facilitating unhindered movement of digital, labor, and capital factors across industries within a given region as well as between different regions. Furthermore, harnessing the positive impact exerted by the digital economy on resource allocation should be fully capitalized upon. Fourthly, there should be an increased investment in the development of the digital economy in the central and Western regions, aiming to bridge the digital gap between these regions and promote inclusive growth within their digital economies.

Based on the findings of this study, it is evident that the impact of the digital economy on industrial structure is more pronounced in the central and Western regions. Therefore, it becomes imperative to fully leverage and support their initial development dividends with increasing marginal returns from their digital economies, thereby unleashing their positive role on regional industrial structures. As for the Eastern region experiencing rapid growth in its digital economy, further optimization of its industrial development environment is necessary to enhance factor allocation efficiency and provide robust support for constructing a modern industrial system.

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