Journal of Economics and Management Sciences; Vol. 8, No. 5; 2025
ISSN 2576-3008 E-ISSN 2576-3016
https://doi.org/10.30560/jems.v8n5p216

Does the Development of the Digital Economy Drive the Growth of Service Consumption? — Evidence from China

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Received: October 21, 2025; Accepted: November 2, 2025; Published: November 3, 2025

Abstract

This paper examines the impact of the digital economy on service consumption using provincial panel data from China (2014–2022) via fixed effects models. The empirical results indicate that the digital economy has a significant positive impact on the growth of service consumption in China. In further heterogeneity analysis, we provide evidence that the digital economy has a significant positive impact on service consumption in eastern China, whereas the positive effect lacks statistical significance in the central and western regions. Notably, the positive effect of the digital economy on service consumption is statistically significant in both rural and urban areas, with the magnitude of the effect being greater in rural areas than in urban areas. Specifically, the digital economy exerts a positive and statistically significant impact on transportation, communication, and healthcare consumption; in contrast, its impact on education, culture, and entertainment consumption is positive yet statistically insignificant. In terms of policy implications, we propose strengthening regional coordination to narrow the digital economy gap, providing preferential allocation of special bonds to the central and western regions, and launching "AI + Education" initiative to develop personalized learning platforms.

Keywords: the digital economy, service consumption, consumption upgrading

1. Introduction

Consumption serves as a foundational cornerstone that underpins economic growth in China. As indicated in the China Statistical Yearbook 2024, the contribution of final consumption to GDP growth amounted to a notable 82.5% in 2023, which drove economic expansion by 4.3 percentage points. Service consumption constitutes not only a key component of aggregate demand but also a critical focal point for boosting consumption growth (see Figure1). From 2014 to 2022, per capita consumption expenditure shows a sustained upward trend. From 14,491 yuan in 2014 to 24,538 yuan in 2022, representing a cumulative increase of 69.3% with an average annual growth rate of approximately 6.8%. And the share of service consumption in total per capita consumption exhibits a generally rising trend with short-term fluctuations. From 2014 to 2019, this share rose steadily from 40.3% to 45.9%, followed by a notable downturn in 2020. Following 2020, the share staged a moderate rebound, though it edged down slightly again in 2022.

Recognizing the significance of service consumption, the Chinese government has attached great importance to its development. Against the backdrop of rising share of the digital economy in China, the 2025 Guidelines on Expanding Service Consumption represent a key policy response to consumption upgrading. However, unlike goods, service consumption is characterized by supply-demand synchronization, difficulty in standardized replication, long-distance transportation characteristics, which poses numerous constraints on the expansion of service consumption. Meanwhile, the digital economy in China is experiencing a trend of rapid development (see Figure2). Specifically, from 2014 to 2022, both the scale of the digital economy and its share in GDP maintained a continuous upward trend. In 2022, the scale of the digital economy reached 50.2 trillion yuan, accounting for 41.5% of GDP. The rapid development of information technology such as big data and artificial intelligence (AI) has spawned new products, new models, and new formats in the service sector, thereby endowing service consumption with enormous growth potential.

In China, the concurrent upward trends of the digital economy and service consumption lend tentative correlational hints to the digital economy's potential role in promoting service consumption. The remainder of the paper is structured as follows: Section 2 presents a literature review. Section 3 outlines the theoretical discussion and research hypotheses. Section 4 elaborates on the adopted data and methodological design. Section 5 reports the empirical results. Section 6 sets out the concluding remarks, policy implications and future research directions.

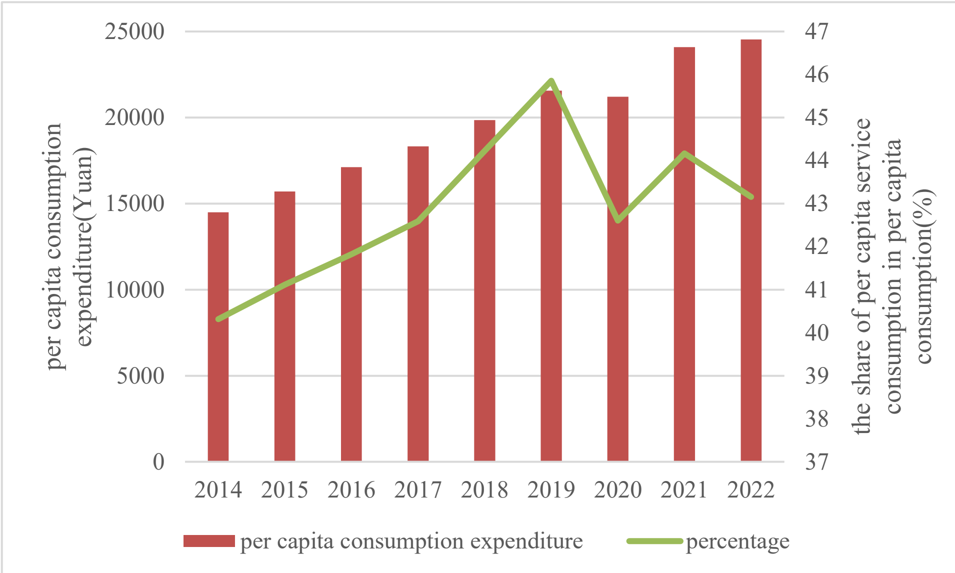

Figure 1. The scale of per capita consumption and the share of per capita service consumption in per capita consumption in China

Source:National Bureau of Statistics

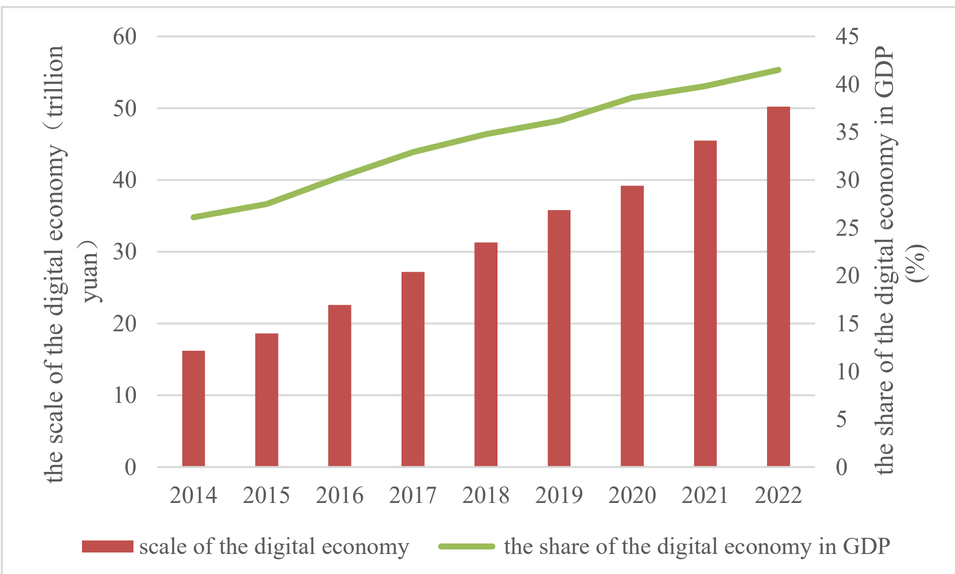

Figure 2. The scale of the digital economy and its share of GDP in China

Source: China Academy of Information and Communications Technology

2. Literature Review

2.1 Determinants of Service Consumption

Existing literature has conducted extensive empirical investigations into the determinants of service consumption in China, with a focus on multiple dimensions including real estate prices (Zeng et al., 2019)[1], the structure of fiscal expenditure (Hu et al., 2025)[2], and the development of public security infrastructure (Liang et al., 2025)[3].

However, these studies have rarely incorporated the digital economy into their analytical frameworks, leaving a noticeable research gap regarding the role of the digital economy in shaping service consumption.

2.2 The Digital Economy and Consumption

In recent years, a growing academic consensus has emerged that the digital economy exerts a positive impact on energy consumption (Xue et al., 2022)[4] and sustainable consumption (Jiang et al., 2024)[5].And Lange et al. (2020)[6] demonstrated that digitalization may lead to additional energy consumption. Guo et al. (2023)[7] further verified that the digital economy plays a facilitative role in both expanding the overall consumption scale and optimizing the consumption structure, providing empirical evidence for the positive correlation between the digital economy and consumption.

2.3 The Digital Economy and Service Consumption

Against the backdrop of the deep integration of the digital economy and the service sector, an increasing number of scholars have focused on their interactive relationship. A series of empirical studies have consistently confirmed that the digital economy exerts a significant positive effect on China's service consumption (Li & Huang, 2022[8]; Yi & Guo, 2023[9]; Xia et al., 2023[10]; Hu et al., 2025[11]).

Although existing research has investigated the determinants of service consumption from diverse perspectives and discussed the digital economy and consumption within the same analytical framework, it exhibits deficiencies in two aspects: first, the measurement of the digital economy is not comprehensive enough; second, the analysis on the heterogeneous impacts of the digital economy on China's service consumption is inadequate. In response to these research gaps, this study constructs a comprehensive index for the digital economy using the entropy method, adds heterogeneity tests across regions, industries, and urban areas.

3. Theoretical Analysis and Hypothesis

Based on existing literature, the digital economy mainly promotes the growth of service consumption by breaking the constraints of service characteristics and reducing transaction costs (see Figure 3). On one hand, the digital economy promotes service consumption by breaking through the constraints of service characteristics. The simultaneity of service production and consumption requires face-to-face interaction between service suppliers and demanders, a constraint that the digital economy can break through via Internet. The digital technologies embodied in the digital economy have broken the spatio-temporal constraints of service production and consumption. Leveraging digital platforms, "long-tail" niche services (e.g., niche language training, rare disease consultation, intangible cultural heritage experiences) can now efficiently reach those in need, even in geographically dispersed areas. The total volume and diversity of service consumption have been enhanced by the digital platforms. Under the conditions of low inventory and distribution costs in the digital economy, the aggregate market share of goods and services with low demand and non-mainstream appeal (i.e., the "Long Tail") can rival that of the mainstream, hit-driven market. Niche and personalized forms of service consumption are on the rise in the digital era (Anderson,2006)[12].

As noted by Choi and Suh (2005) [13], Nakayama (2008)[14], and Sun et al. (2017)[15], the development of the Internet breaks the spatio-temporal constraints, facilitate consumers and suppliers in concluding transactions without spatial distance, and thereby boost consumption.

On the other hand, the digital economy promotes service consumption by reducing specific transaction costs such as search costs, the costs incurred by consumers to find suitable service providers or product information. Specifically, market transactions involve multiple types of costs beyond search costs, which may include negotiation costs, contract enforcement costs, and post-transaction maintenance costs(Coase,1937).[16]The intangibility and heterogeneity of service consumption increase information asymmetry between suppliers and consumers, resulting in significantly higher transaction costs compared to goods consumption. Platforms lower transaction costs for the price-sensitive side that is critical for attracting the other (typically consumers) by implementing a skewed pricing strategy that offers them discounts or subsidies (Rochet & Tirole,2003)[17].

Trust has become as critical a dimension as technology in online transactions (Gefen et al.,2003)[18]. Digital platforms create a foundation of trust for large-scale transactions between strangers through socio-technical tools such as rating systems, review mechanisms, identity verification, and insurance guarantees (Sundararajan,2017) [19]. As Jiang (2017) [20] noted, Internet platforms can not only facilitate direct transactions between producers and consumers, but also aggregate dispersed and personalized signals, and help consumers access fields with high professional barriers to obtain relevant information.

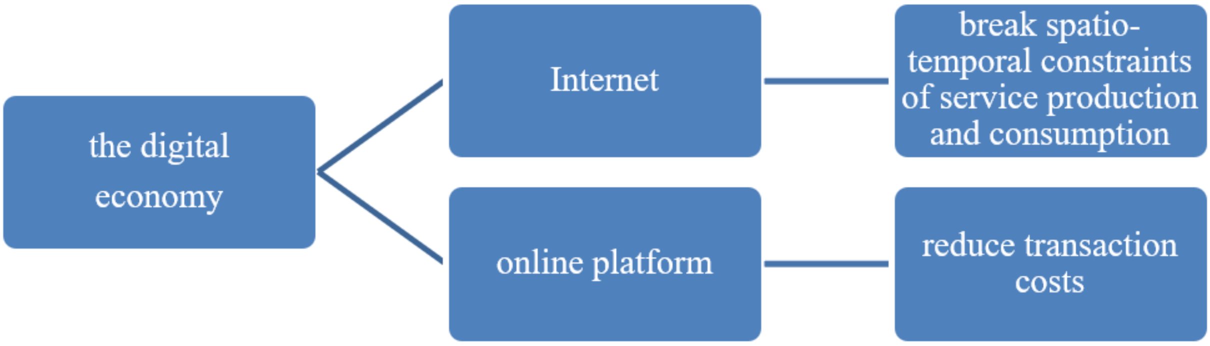

Figure 3. The Mechanism by Which the Digital Economy Drives Service Consumption.

Based on the above discussion, the following hypothesis (H) is proposed as follows:

H: The development of the digital economy promotes the growth of service consumption.

4. Data and Methods

4.1 Sample and Data Sources

This paper uses panel data from 31 provinces, administrative regions, including provinces, municipalities directly under the Central Government, and autonomous regions in China over the period 2014-2022. The data are mainly obtained from the National Bureau of Statistics of China (NBSC), the China Statistical Yearbook, the Peking University Digital Inclusive Finance Index and Provincial Statistical Yearbooks.

4.2 Variables and Measurement

4.2.1 Dependent Variable

The dependent variable of this study is per capita service consumption($SC_{\text{per capita},i,t}$). The per capita service consumption is defined as the sum of transportation and communication consumption, education, culture, and entertainment consumption, medical and health care consumption. And per capita service consumption expenditure over the period 2015-2022 is deflated using the Consumer Price Index (CPI) to the 2014, eliminating the impact of price fluctuations across years, converting nominal residential service consumption expenditure into real expenditure that reflects changes in actual consumption volume. The per capita service consumption is calculated through population-weighted averaging, where the per capita service consumption of urban and rural residents are weighted by their respective population proportions in the total population of the province. The specific formula is as follows:

$$SC_{\text{per capita},i,t} = SC_{\text{urban},i,t} \times \alpha_{i,t} + SC_{rural,i,t} \times (1 - \alpha_{i,t})$$

Where $SC_{\text{per capita},i,t}$ is per capita service consumption expenditure in province i at time t, $SC_{\text{urban},i,t}$ is average service consumption expenditure per urban resident in province i at time t, $SC_{rural,i,t}$ is average service consumption expenditure per rural resident in province i at time t, $\alpha_{i,t}$ is the proportion of urban resident population in the total resident population of province i at time t, (calculated as $\frac{Urban\ Population_{i,t}}{Total\ Population_{i,t}}$), $(1 - \alpha_{i,t})$ is the proportion of rural resident population in the total resident population of province i at time t (since the sum of urban and rural population proportions equals 1, this term avoids redundant calculation of rural population data).

4.2.2 Independent Variable

The independent variable of this study is the digital economy(DE). Follow the method of Wang et al.(2021)[21], we develop a composite index that takes digital infrastructure, digital industrialization, and industrial digitalization into account (see Table 1) to measure the level of the digital economy using the entropy method. The calculation of the Entropy Weight Method (EWM) is divided into five steps.

Firstly, standardize the indicator data. Since indicators have different dimensions, min-max standardization is used to eliminate the impact of unit differences. For positive indicators (higher values indicate better development), the formula is:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

For negative indicators (lower values indicate better development, if any), the reciprocal transformation is first performed, then standardized using the above formula. Where x'_{ij} is standardized value of the j-th indicator in the i-th province, x_{ij} is original value of the j-th indicator in the i-th province, $\max(x_j)$ *and* $\min(x_j)$ are maximum and minimum values of the j-th indicator across all provinces.

Secondly, calculate the indicator proportions (p_{ij}). Compute the proportion of the standardized value of each indicator in the total value of that indicator across all samples, reflecting the relative importance of the i-th sample in the j-th indicator. The formula is:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}}$$

Where n is the number of samples, and $p_{ij} \geq 0$. If $p_{ij} = 0$, add a small constant to avoid undefined values in the logarithmic calculation.

Thirdly, calculate the indicator entropy values e_j .The entropy value of the j-th indicator is calculated to measure its information dispersion. The formula is:

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} P_{ij} . \ln (P_{ij})$$

The e_j ranges from 0 to 1, with smaller e_j denoting higher dispersion and stronger information utility of the indicator.

Fourthly, calculate the indicator weights w_j. Determine the weight of each indicator based on its information utility value$(1 - e_j)$. The formula is:

$$w_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)}$$

Where m is the number of indicators, and $\sum_{j=1}^{m} w_j = 1$.

Fifthly, construct the comprehensive index. Multiply the standardized value of each indicator by its corresponding weight, and sum the results to obtain the comprehensive index of the evaluated object. The formula is:

$$DE_i = \sum_{j=1}^{m} w_j . x'_{ij}$$

Where DE_i is the digital economy development index of the i-th province.

Table 1. Measurement of the Digital Economy

First-level Indicator	Second-level Indicator	Measurement	Attribute
Digital Infrastructure	Internet Broadband Access Rate	The percentage of the number of Internet broadband access ports among the total number of permanent residents	+
	Internet Broadband Popularization Rate	The percentage of the number of Internet broadband access users among the total number of permanent residents	+
	Scale of Mobile Phone Facilities	Capacity of mobile telephone exchanges	+
	Length of Long-distance Optical Cable Lines	Length of Long-distance Optical Cable Lines	+
	Number of Webpages	Number of Webpages	+
	Number of Domain Names	Number of Domain Names	+

Digital Industrialization	Total Telecommunications Business Volume per Capita	The percentage of total telecommunications business volume among the total number of permanent residents	+
	Mobile Phone Popularization Rate	Mobile Phone Popularization Rate	+
	Number of Legal Entities in Information Transmission, Software and IT Services	Number of Legal Entities in Information Transmission, Software and IT Services	+
	Proportion of Employees in Information Software Industry	The percentage of number of employees in urban units of information transmission, software and IT services among the total number of employees in urban units	+
	Number of Authorized Domestic Patent Applications	Number of Authorized Domestic Patent Applications	+
	Number of Accepted Domestic Patent Applications	Number of Accepted Domestic Patent Applications	+
Industrial Digitalization	PKU Digital Inclusive Finance Index	PKU Digital Inclusive Finance Index	+
	Proportion of Enterprises with E-commerce Transactions	Proportion of Enterprises with E-commerce Transactions	+
	E-commerce Sales	E-commerce Sales	+
	Number of Websites per 100 Enterprises	Number of Websites per 100 Enterprises	+
	Added Value of Secondary and Tertiary Industries	The sum of added value of the secondary industry and added value of the tertiary industry	+
	Investment in Scientific and Technological Innovation	R&D expenditure of industrial enterprises above a designated size	+
	Express Volume	Express Volume	+

4.2.3 Control Variables

The control variables are selected based on prior scholarly works examining the determinants of service consumption (see Table2). We first include per capita disposable income(PCI) in our model. The calculation of PCI is similar to that of per capita service consumption mentioned above. Included in the second set of control variables are the Child Dependency Ratio (CDR) and the Elderly Dependency Ratio (EDR).CDR is the proportion of the 0-14 age group in the 15-64 age group, and EDR is the proportion of the 60-and-above age group in the 15-64 age group. The natural logarithm of GDP per capita (ln pgdp) is also incorporated to control for the general level of economic development. We further include the natural logarithm of General Public Budget Expenditure (denoted as lnGPBE) in the model to account for the scale of fiscal expenditure. This study converts US dollars into Chinese Yuan (CNY) based on the annual average CNY exchange rate of the corresponding year. In Table 3 we provide some descriptive statistics of the variables that we include in this study.

Table 2. Variable Measurement and Data Sources

Variable	Measurement	Unit	Source
Dependent Variable			
Service Consumption(SC)	$\mathrm{SC}_{\mathrm{urban,i,t}} \times \alpha_{\mathrm{i,t}} + \mathrm{SC}_{rural,i,t} \times (1 - \alpha_{\mathrm{i,t}})$ Where αis the proportion of urban resident population in the total resident population of province	Yuan	China Statistical Yearbook
Independent Variable			
the Digital Economy(DE)	Adopt the Entropy Weight Method, with specific indicators shown in Table 1	-	Provincial Statistical Yearbooks, the Peking University Digital Inclusive

			Finance Index
Control Variables			
Per Capita disposable Income(PCI)	$PCI_{urban,i,t} \times \alpha_{i,t} + PCI_{rural.i.t} \times (1-\alpha_{i,t})$	Yuan	China Statistical Yearbook
Child Dependency Ratio(CDR)	the proportion of the 0-14 age group in the 15-64 age group	Percentage	China Statistical Yearbook
Elderly Dependency Ratio(EDR)	the proportion of the 60-and-above age group in the 15-64 age group	Percentage	China Statistical Yearbook
The scale of fiscal expenditure (GPBE)	general public budget expenditure	Yuan	China Statistical Yearbook
The level of economic development (pgdp)	GDP per capita	Yuan	China Statistical Yearbook

Table 3. Descriptive Statistics

Variable	Obs	Mean	SD	Min	Median	Max
lnSC	279	8.798	0.375	7.196	8.846	9.692
lnDE	279	-2.108	0.641	-3.415	-2.161	-0.353
lnPCI	279	10.212	0.359	9.324	10.197	11.263
ln CDR	279	3.130	0.295	2.485	3.199	3.648
ln EDR	279	2.761	0.285	1.947	2.764	3.359
lnGPBE	279	8.530	0.590	6.908	8.570	9.827
ln pgdp	279	10.972	0.422	10.131	10.911	12.156

4.3 Model Specification

The empirical results from the fixed effects model are reported herein, and the corresponding estimator is formulated as follows:

$$\mathrm{lnSC}_{i,t} = \beta_0 + \beta_1 \mathrm{lnDE}_{i,t} + \beta_2 \ln \mathrm{PCI}_{i,t} + \beta_3 \ln \mathrm{CDR}_{i,t} + \beta_4 \ln \mathrm{EDR}_{i,t} + \beta_5 \ln \mathrm{pgdp}_{i,t} + \beta_6 \ln \mathrm{GPBE}_{i,t} + \mu_i + \lambda_i + e_{i,t} \quad (1)$$

All variables are incorporated in their natural logarithmic forms to mitigate heteroscedasticity, where: $\mathrm{lnSC}_{i,t}$ denotes per capita service consumption of province i at time t;$\mathrm{lnDE}_{i,t}$ the digital economy level; $\ln \mathrm{PCI}_{i,t}$ the income level;$\ln \mathrm{CDR}_{i,t}$ the child dependency ratio; $\ln \mathrm{EDR}_{i,t}$ the elderly dependency ratio;$\ln \mathrm{pgdp}_{i,t}$ per capita GDP; and $\ln \mathrm{GPBE}_{i,t}$ general public budget expenditure—with all indicators corresponding to province i at time t. μ are province fixed effects, λ are time effects, $e_{i,t}$ is an error term.

As shown in Table 4, the variance inflation factors (VIF) for both the independent variable and control variables are below 10, indicating that there is no serious multicollinearity among the variables.

Table 4. Multicollinearity Test

Variable	VIF
DE	8.10
PCI	8.58
CDR	1.29
EDR	1.60
GPBE	5.16
pgdp	8.18

5. Empirical Results

5.1 Benchmark Regression Analysis

Table 5 presents the empirical results of the determinants of service consumption over the period 2014-2022. Columns (1)-(2) in Table 5 report the fixed effects estimation results. Specifically, a 1% increase in the digital economy leads to a 0.670% rise in service consumption without adding control variables, and this effect is statistically significant at the 1% level. After incorporating control variables, a 1% growth in the digital economy contributes to a 0.099% increase in service consumption, with the effect remaining statistically significant at the

1% level. It is indicated that the digital economy (lnDE) has a significant positive impact on service consumption both before and after the inclusion of control variables.

Table 5. Benchmark Regression Results on the Impact of the Digital Economy on Service Consumption (2014-2022)

	(1) lnSC	(2) lnSC
lnDE	0.670***	0.099***
	(23.967)	(3.322)
lnPCI		0.894***
		(11.294)
lnCDR		-0.150
		(-1.621)
lnEDR		-0.207***
		(-4.039)
lnpgdp		0.214*
		(2.026)
lnGPBE		0.133
		(1.260)
Constant	10.210***	-2.567***
	(173.318)	(-3.689)
Time effects	Yes	Yes
Province effects	Yes	Yes
Observations	279	279

*p<0.1, **p<0.05, ***p<0.01. T statistics are in parentheses.

5.2 Endogeneity Tests

Given potential bidirectional causality between the digital economy and service consumption, we mitigate endogeneity via two strategies: lagging the core independent variable (the digital economy) by one period, and lagging the dependent variable (service consumption) and controls by 1–2 periods. Columns (1)–(3) in Table 6 present the endogeneity test results. Column (1) shows that the one-period lagged core independent variable (L.lnDE) has a statistically significant positive coefficient at the 1% level. Specifically, a 1% increase in the digital economy drives a 0.125% growth in service consumption. Column (2) reports that lnDE yields a statistically significant positive coefficient at the 1% level when the dependent variable (service consumption) and control variables are lagged by one year. Column (3) indicates that the coefficient remains statistically significant at the 5% level when they are lagged by two years. These results confirm the robustness of our core conclusion that the development of the digital economy promotes the growth of service consumption in China.

Table 6. Endogeneity tests

	(1) first-lagged term of DE	(2) first-lagged excluding DE	(3) second-lagged excluding DE
L.lnDE	0.125***		
	(3.655)		
lnPCI	0.790***		
	(12.409)		
lnCDR	-0.186*		
	(-1.872)		
lnEDR	-0.242***		
	(-5.148)		
lnpgdp	0.227*		
	(1.978)		
lnGPBE	0.130		

	(1.066)		
lnDE		0.156***	0.083**
		(5.153)	(2.726)
L.lnPCI		1.282***	
		(7.708)	
L.lnCDR		-0.228***	
		(-3.054)	
L.lnEDR		-0.118*	
		(-1.974)	
L.lnpgdp		-0.101	
		(-0.639)	
L.lnGPBE		-0.051	
		(-0.503)	
L2.lnPCI			1.302***
			(6.874)
L2.lnCDR			-0.381***
			(-3.389)
L2.lnEDR			-0.142*
			(-1.737)
L2.lnpgdp			-0.123
			(-0.687)
L2.lnGPBE			0.122
			(0.963)
Constant	-1.330	-1.393	-2.453**
	(-1.363)	(-1.694)	(-2.493)
Time effects	Yes	Yes	Yes
Province effects	Yes	Yes	Yes
Observations	248	248	217

*p<0.1, **p<0.05, ***p<0.01. T statistics are in parentheses.

5.3 Heterogeneity Tests

5.3.1 Regional Heterogeneity Test

Given the imbalance of regional development in China, in accordance with the classification standards of the National Bureau of Statistics of China (NBSC), we divide the sample into three major regions (eastern, central, and western). Column (1) in Table 7 shows the digital economy has a significant positive effect on service consumption at the 10% level in eastern China while Column (2)-(3) in Table 7 shows the effect of the digital economy (lnDE) on service consumption is positive but not statistically significant in central and western regions. The observed variations in empirical findings can be ascribed to the following factors. Firstly, the eastern region has a leading competitiveness in new infrastructure compared with the central and western regions in China. Eastern regions have long maintained advantages in indicators such as 5G base station coverage rate and fiber-to-the-home penetration rate, which supports the high-efficiency penetration of services like e-commerce and mobile payments. Secondly, the digital literacy and skills of residents in the eastern region are significantly better than those in the central and western regions. Residents in the east are more accustomed to purchasing services such as education, healthcare, and culture through online platforms, while residents in the central and western regions may still rely on offline channels due to inadequate operational proficiency or insufficient trust. Thirdly, there are differences in industrial structure between the eastern region and the central and western region. The service industry in the east has achieved deep integration with the digital economy—the proportion of the service industry in GDP in eastern regions generally exceeds 60%, and it is dominated by high-end service industries such as finance, information technology, and cultural and creative industries, which are naturally suitable for digital transformation. In contrast, the service industry in the central and western regions is still dominated by traditional commerce and transportation, and lags in digital transformation.

Table 7. Regional Heterogeneity Test

	(1) Eastern	(2) Central	(3) Western
lnDE	0.138*	0.034	0.048
	(2.056)	(0.337)	(0.993)
lnPCI	0.802***	1.924***	1.063***
	(12.120)	(8.234)	(3.996)
lnCDR	-0.408	-0.307	-0.098
	(-1.691)	(-1.440)	(-0.775)
lnEDR	0.041	-0.428**	-0.212**
	(0.352)	(-3.005)	(-2.418)
lnpgdp	0.158	-0.242	-0.049
	(0.688)	(-1.244)	(-0.188)
lnGPBE	0.007	-0.053	0.319
	(0.051)	(-0.231)	(1.558)
Constant	0.062	-5.395*	-3.103***
	(0.026)	(-2.284)	(-3.417)
Time effects	Yes	Yes	Yes
Province effects	Yes	Yes	Yes
Observations	90	72	108

*p<0.1, **p<0.05, ***p<0.01. T statistics are in parentheses.

5.3.2 Urban-Rural Heterogeneity Test

With regards to the urban-rural imbalances in China, we respectively provide the empirical results of the effect of the digital economy on service consumption in Table 8. Column (1) - (2) in Table8 show that the digital economy (lnDE)promotes the growth of service consumption both in rural and urban areas at the 1% and 10% significance levels, respectively, but the effect in rural areas is stronger than urban areas. A key driver is the late-mover advantage in rural areas, particularly with respect to infrastructure gap-filling and targeted policy support. For growth drivers, the base of rural service consumption is relatively lower than urban regions, thus the application of digital technology is more likely to bring about breakthroughs “from scratch”. In terms of infrastructure, the effect of digital infrastructure gap-filling in rural areas is significant. Rural areas have achieved “leapfrog development” through policy preferences, despite of the leading advantage of urban digital infrastructure. In contrast, the urban logistics network has become mature, and the marginal driving effect of digital infrastructure on service consumption has weakened. From the perspective of policy orientation, the government has directly promoted the expansion of rural service consumption through policies such as “Digital Commerce for Rural Revitalization” and “Internet + Agricultural Products Going Out of Villages and Entering Cities”.

Table 8. Heterogeneity Test of Urban and Rural

	(1) Rural	(2) Urban
lnDE	0.119***	0.063*
	(3.506)	(1.842)
$lnPCI_{rural}$	1.192***	
	(4.346)	
lnCDR	-0.256**	-0.224**
	(-2.397)	(-2.648)
lnEDR	-0.230***	-0.195***
	(-5.068)	(-4.464)
lnpgdp	0.077	-0.170
	(0.311)	(-1.019)
lnGPBE	0.168	0.017
	(1.308)	(0.174)
$lnPCI_{urban}$		1.416***
		(6.429)

Constant	-3.667***	-2.739***
	(-4.000)	(-3.586)
Time effects	Yes	Yes
Province effects	Yes	Yes
Observations	279	279

*p<0.1, **p<0.05, ***p<0.01. T statistics are in parentheses.

5.3.3 Industrial Heterogeneity Test

Table 9 shows the results of the effect of digital economy on different service consumption. Column (1) and (3) in Table 9 reveal a positive and significant at the 1% level effect on transportation and communication and healthcare while Column (2) in Table 9 shows the effect of digital economy on education, culture and entertainment is positive but not statistically significant. The factors contributing to this discrepancy are outlined as follows. First, the digital economy has achieved in-depth integration with intelligent infrastructure and mobility services, fundamentally transforming the underlying logic of transportation and communication consumption. Technological applications represented by 5G, Beidou Navigation, and vehicle-to-everything (V2X) have driven the explosive growth of new business formats such as ride-hailing, bike-sharing, and intelligent logistics. Meanwhile, telemedicine, the popularization of smart devices, and the digitalization of medical insurance have amplified the facilitating effect of the digital economy. In contrast, the digitalization process in the education, culture, and entertainment sector is relatively slow, mainly constrained by its reliance on in-person experiences and insufficient supply-side innovation.

Table 9. Industrial heterogeneity Test

	(1) Transportation and Communication	(2) Education, Culture and Entertainment	(3) Healthcare
lnDE	0.146***	0.060	0.186***
	(4.155)	(1.191)	(3.613)
lnPCI	0.353**	0.544***	0.286**
	(2.473)	(3.272)	(2.241)
lnCDR	-0.086	-0.265	0.240***
	(-0.768)	(-1.694)	(2.816)
lnEDR	-0.150*	-0.347***	-0.183***
	(-1.777)	(-5.213)	(-2.774)
lnpgdp	0.527***	0.421**	0.940***
	(3.136)	(2.574)	(5.947)
lnGPBE	0.207	0.299*	0.108
	(1.674)	(1.735)	(0.849)
Constant	-2.299*	-3.167***	-6.602***
	(-2.033)	(-2.999)	(-6.886)
Time effects	Yes	Yes	Yes
Province effects	Yes	Yes	Yes
Observations	279	279	279

*p<0.1, **p<0.05, ***p<0.01. T statistics are in parentheses.

6. Conclusion

From the perspectives of breaking through the constraints of service characteristics and reducing transaction costs, this study analyzes the theoretical mechanism by which the digital economy shapes service consumption. This study empirically demonstrates that the digital economy has a significant positive impact on service consumption. In further analysis, we provide evidence that the digital economy has a positive and significant effect on service consumption in the eastern regions, while the positive effect is not statistically significant in the central and western regions. The positive effect of the digital economy on service consumption is statistically significant both in rural and urban areas, but the effect in rural areas is stronger than that in urban areas. The digital economy has a positive and significant effect on transportation, communication, and healthcare, whereas the effect of the digital economy on education, culture, and entertainment is positive but not statistically significant.

These empirical results have some important policy implications. It is necessary to strengthen regional coordination and narrow the digital economy gap. Key infrastructure such as 5G base stations and industrial Internet identification resolution nodes should be included in the key priorities for new infrastructure investment. Preferential allocation of special bonds should be given to central and western region to support these regions in undertaking the transfer of digital industries from the eastern regions. Furthermore, it is essential to break through bottlenecks and unleash the consumption potential of education, culture, and entertainment services. The "AI + Education" initiative should be launched to develop personalized learning platforms, which can analyze students' learning data through large models and provide targeted tutoring programs.

This study is subject to several inherent limitations that should be acknowledged. First, this study did not incorporate prefecture-level data, which may lead to the oversight of intra-regional differences. Second, endogeneity treatment via lagging variables was modest. Third, the theoretical mechanism failed to achieve formalized expression through explicit functional forms or mathematical derivations, and was confined to the level of qualitative description.

Future research efforts can be extended in the following directions: First, integrate micro-survey data to analyze the heterogeneous impacts of the digital economy on service consumption across different income groups. Second, add robustness checks such as instrumental variable (IV) or system GMM estimation to improve the endogeneity section. Third, theoretical mechanism could be expanded via explicit functional forms.

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