Urban Resilience and Sustainability

Urban Resilience Sustainability, 2(4): 307–325.
DOI: 10.3934/urs.2024016
Received: 10 August 2024
Revised: 26 September 2024
Accepted: 17 October 2024
Published: 31 October 2024

https://www.aimspress.com/journal/urs

Research article

Research on the impact of digital trade and energy consumption

Siyu Zhang[1], Songlan Zhou[2,*], Mengxin Wang[3] and Leyan Zuo[1]

[1] School of Economics and Statistics, Guangzhou University, Guangzhou, 510006, China
[2] Guangzhou College of Applied Science and Technology, Guangzhou, 511370, China
[3] Institute of Finance, Guangzhou University, Guangzhou, 510405, China

* **Correspondence:** Email: sesslzhou@gzhu.edu.cn; Tel: +18933928468.

Abstract: This study investigates the impact of the digital trade on energy consumption, as well as its mechanism, from 2014 to 2022 by developing a digital trade evaluation index system. We find that the growth of the digital trade can reduce per capital energy consumption and also passes various robustness tests. The main influencing mechanism is that the digital trade affects energy structure transformation and changes in final demand, which results in lower energy consumption. In terms of the spatial distribution, the digital trade decreases per capital energy consumption more in the eastern regions and promotes per capital energy consumption reduction less in the central regions, whereas there is no significant correlation in the western regions. The findings extend the benefits of the digital trade beyond economic and social welfare benefits and provide a consultation for digital economy for green development.

Keywords: digital trade; energy consumption; benchmark regression; PCA; 21th century; provincial areas

1. Introduction

In the wave of digitization and globalization, traditional trade has evolved into a new form of commerce—digital trade—by integrating with digital technologies. As a crucial component of the digital economy, digital trade has profoundly transformed the traditional trade mode and business model due to its efficiency and convenience. It transcends temporal and spatial constraints, enabling rapid circulation of goods and services, unprecedented convenience for global consumers and businesses alike. According to the World Trade Organization (WTO), global exports of digitally deliverable services reached $4.1 trillion in 2022, accounting for 57.1% of global service exports. Countries worldwide have made great breakthroughs in digital ordering trade and digital technology innovation. Developing countries, particularly emerging economies, exhibit substantial growth potential in digital service exports, with China ranking prominently among developing nations in digitally deliverable service imports and exports. However, the rapid expansion of digital trade has brought to the forefront issues related to energy consumption. As the world's largest producer and consumer of energy, China's total energy consumption reached 5.41 billion tons of standard coal equivalent in 2022, marking a 2.9% increase from the previous year, according to the "China Energy Big Data Report (2023)." This rise in energy consumption exacerbates global energy scarcity, environmental pollution, and climate change. Thus, guided by goals such as peak carbon emissions and carbon neutrality, China continues to promote green and low-carbon transformations, enhance the consumption of clean and low-carbon energy, improve energy efficiency across industries, and advocate for greener and more sustainable lifestyles. Given these circumstances, investigating whether digital trade can reduce energy consumption, and understanding how it achieves this reduction, is of significant theoretical and practical importance. This paper aims to explore the impact of digital trade on energy consumption through theoretical analysis and empirical research, uncovering the underlying mechanisms and providing recommendations for the sustainable development of digital trade.

1.1. Literature review

1.1.1. The connotation of digital trade

There is no unified definition of digital trade in academia. The concept of digital trade was first proposed by the American scholar Weber 0, who defined it as commercial activities conducted via the internet. This concept has been expanded and extended by different countries, organizations and scholars in subsequent studies. According to the Organisation for Economic Co-operation and Development (OECD), digital trade refers to all trade in goods and services ordered or delivered digitally. This definition emphasizes the essence of trade, that is, indicating that any trade conducted digitally, whether ordering or delivery, falls within the scope of digital trade. Most scholars, both domestic and international, compare digital trade with traditional trade to define digital trade. For example, Ma Shuzhong 0 considered digital trade as the expansion and extension of traditional trade in the era of digital economy, emphasizing the use of modern information networks and communication information technologies to efficiently exchange traditional goods, digital products and services, and digitized knowledge and information. In 2019, the China Academy of Information and Communications Technology (CAICT) released the "White Paper on the Development and Impact of Digital Trade," which elaborates on the concept of digital trade. This form of trade is characterized by the significant role of digital technology. The primary distinction between digital trade and traditional trade lies in the digitization of both trade methods and trade objects.

1.1.2. Measurement of digital trade

Regarding the measurement of digital trade, most domestic scholars have measured the development level of national (or regional) digital trade by constructing a digital trade evaluation index system. Since digital trade is based on e-commerce, cross-border e-commerce, and the digital economy, its development level is largely influenced by these three factors. Li Wei 0 analyzed the development mechanism of digital trade in China and divided its development level into four subsystems: Digital infrastructure, digital technology innovation, key industry development, and digital trade potential. Li asserted that these four subsystems directly promote the reconstruction of trade models. Zhang Yafei 0 developed an evaluation system for digital trade development from four dimensions: digital technology application, digital trade mode, digital trade capacity, and trade potential, using 17 secondary indicators. Pei Guifen 0 constructed a digital trade development evaluation index system from five perspectives: Infrastructure level, digital technology level, trade digitalization capability, digital trade objects, and trade potential, refining it to 26 sub-indicators.

1.1.3. Influencing factors of energy consumption

The influencing factors of energy consumption in the existing domestic literature can be roughly divided into the following categories: Economic factors, industrial structure factors, policy factors, technological factors, and demographic factors. In terms of economic factors, Shen Bing 0 discovered through an experimental study that the advanced industrial structure can function as a mediating variable, transmitting the impact of financial development to energy efficiency improvement. Ultimately, this can facilitate energy conservation and consumption reduction. In terms of policy factors, Zou Ganna 0 investigated the relationship between environmental regulations and energy consumption. Using a difference-in-differences approach, Zou effectively identified the net effect of environmental tax implementation and examines the mechanism through which environmental taxes influence energy consumption. Wang Jun 0 empirically analyzed the effects of trade liberalization on energy consumption, finding that trade liberalization reduces energy consumption intensity through energy-saving technological progress. In terms of technical factors, Lang Chunlei 0 suggested that the long-term impact of technological innovation on energy consumption follows a U-shaped relationship, indicating a rebound effect in China's energy consumption due to technological innovation, although current technological development has not yet reached the critical threshold. However, Hou Guisheng 0 incorporated environmental regulations, technological innovation, and energy consumption into a unified research framework, revealing that environmental regulations have a short-term inhibitory effect on energy consumption, while technological innovation exerts a long-term inhibitory effect.

Many scholars have studied the relationship between industrial structure transformation and energy consumption, often employing traditional linear models. Fu Zihao 0 used a nonlinear model to investigate this relationship, finding an inverted U-shaped relationship between industrial structure transformation and energy consumption. Additionally, improved local government governance facilitates faster entry into the energy consumption reduction phase. Li Bizhen 0 argues that the current stage of manufacturing servitization has not significantly reduced energy consumption in China's manufacturing sector. While the input of productive service factors significantly reduces energy consumption, differences in the division of labor within the manufacturing industry negatively moderate this reduction effect. These articles provide a reference for selecting control variables in this paper.

1.1.4. Digital economy and energy consumption

The existing literature on digital trade and energy consumption is relatively sparse, with most scholars focusing on the relationship between the digital economy and energy factors. Various researchers have explored the impact of the digital economy on factors such as total factor energy efficiency, energy factor misallocation, urban energy utilization efficiency, energy structure transformation, energy security, energy intensity, industrial structure upgrading, energy efficiency, and energy productivity. Among these, studies examining the relationship between the digital economy and industrial structure upgrading are the most prevalent. Some researchers have approached the topic from a green and low-carbon perspective. For instance, Zhao Tingting 0 explored the impact of green finance on the energy consumption structure, arguing that green finance can significantly improve the energy consumption structure through three paths: Optimizing the industrial structure, enhancing energy efficiency and promoting green innovation. Sun Fei 0 focused on the low-carbon transition of traditional energy industries, finding through empirical research that digital empowerment exhibits an inverted "U-shaped" relationship with the low-carbon transition of traditional energy industries, with a significant positive long-term impact from digital talent on this transition.

Other scholars have studied the intersection of digital trade, green development, and industrial green transformation. Xie Huiqiang 0 identified the demand-induced effect as an indirect pathway for digital trade to reduce carbon emissions and, from a spatial spillover perspective, concludes that the level of digital trade in a province negatively impacts the carbon reduction intensity of neighboring provinces. Wen Chujian 0 posited that digital trade can indirectly enhance the green efficiency of China's logistics industry through material and human capital, thereby promoting the green transformation of the logistics sector.

In addition, some international literature discusses the relationship between digital trade and energy factors, such as Fan Bi 0 discussed how the digital economy affects the urban energy structure and found that the digital economy improves the urban energy structure by weakening the dependence on urban resources. Liu Xiaoqian 0 believed that the digital economy accelerates marketization by promoting industrial structure upgrading and technological progress, thereby reducing energy consumption. Zhu Yumin 0 examined the impact of the development of China's digital economy on its carbon neutrality strategy, and also explores whether this relationship is consistent with the environmental Kuznets curve hypothesis.

In summary, with the vigorous development of the digital economy, some scholars have increasingly focused on the impact of the digital economy on energy factors, conducting both theoretical and empirical analyses of its transmission pathways. However, there is a notable scarcity of literature that integrates digital trade and energy consumption within a unified framework. Therefore, the innovation of this paper is as follows: First, this paper provides a theoretical and empirical analysis of the relationship between digital trade and energy consumption, and explores deeply its path in depth. Second, the heterogeneity analysis of the impact of digital trade on energy consumption expands the research content of relevant literature. Third, according to the impact of digital trade on energy consumption, corresponding policy recommendations are put forward to help China's sustainable energy development. Based on this, this paper incorporates the development level of digital trade and energy consumption into the analytical framework. It explores the relationship between digital trade and energy consumption from theoretical and empirical perspectives, further proposes the realization path of digital trade to reduce energy consumption, and analyzes the heterogeneity of digital trade on energy consumption.

1.2. Theoretical analysis and research hypothesis

1.2.1. Analysis of the direct effect of digital trade on energy consumption

Utilizing digital technology, digital trade can effectively improve transaction efficiency, reduce transaction costs for two or more parties, and directly promote the reduction of energy consumption levels. Digital trade may curb energy consumption in two ways: On the one hand, digital trade results from the continuous integration and penetration of digital technology and traditional trade. Compared with traditional trade, digital trade is characterized by virtualization, platformization, intensification, inclusiveness, and personalization, representing the digitization of various stages of traditional trade.

In the production and manufacturing phase, digital trade products and services use digital technology to achieve efficient control of the production process and optimization of energy consumption, so as to improve production efficiency and prevent unnecessary energy waste. In the process of trading, supply and demand parties conduct online transactions via internet platforms, changing the traditional trade process that requires physical delivery at specific offline locations, reducing the need for intermediaries such as agents and wholesalers, effectively decreasing logistics and transportation demands in physical trade, and reducing energy consumption. Moreover, digital trade promotes the development of green logistics, utilizing digital information systems and digital supply chain systems to monitor the movement of goods in real-time, accurately arrange transportation routes, avoid empty runs and repetitions, enhance transportation efficiency, and reduce energy consumption during transportation. Second, digital trade, through the intermediary platform of the internet, lowers China's trade barriers, expands global trade space, alters the form and flow of international trade, and introduces foreign digital products and services to foster healthy competition for domestic digital products. By introducing foreign products and services, the domestic supply side faces more market competition pressure, encouraging the supply side to improve its technological level and production efficiency, reducing unnecessary energy consumption. Market competition also drives domestic manufacturing enterprises to focus more on product quality and performance, promoting the development of traditional industries towards high-end, aiding in reducing resource wastage and energy consumption. Simultaneously, the development of digital trade also attracts more enterprises to explore new markets, providing more opportunities for the development of small and medium-sized enterprises in China. As global environmental awareness increases, more countries begin to focus on green trade and sustainable development. To enhance competitiveness in the international market, domestic export-oriented enterprises are inclined to export environmentally friendly products produced with clean energy, reducing dependence on fossil energy and lowering the consumption of non-renewable energy. Based on the above analysis, this paper proposes the first research hypothesis:

Hypothesis 1: Digital trade has an inhibitory effect on energy consumption.

1.2.2. Analysis of the indirect effect of digital trade on energy consumption

Digital trade can also inhibit energy consumption indirectly by changing the energy consumption production and consumption modes, promoting energy consumption reduction. First, at the energy consumption end, the rise of digital trade not only optimizes the energy consumption structure but also promotes innovation in energy consumption modes. From the perspective of enterprises, using high-cost, high-pollution non-renewable resources for production activities no longer aligns with the green development concept and enterprise development needs. By improving production technology, enterprises shift to using renewable resources, promoting the energy structure towards an environmentally friendly direction. From the perspective of residents, the digital economy helps strengthen residents' awareness of green living, guiding them to choose more low-carbon and environmentally friendly lifestyles and products in daily life, thereby reducing energy consumption at the household level. Moreover, under the promotion of digital trade, new energy consumption modes such as the sharing economy and the energy internet are emerging, helping to unblock collaborative innovation points among enterprises in raw materials, production equipment, and monitoring equipment, achieving resource sharing and value maximization, reducing resource wastage caused by information asymmetry, and improving enterprise energy use efficiency. Second, at the energy production end, digital transformation drives energy-intensive industries towards digital and intelligent development. On one hand, relying on digital means, energy production enterprises continuously optimize the extraction, processing, and packaging processes of energy, achieving dynamic and efficient energy production processes. On the other hand, as the degree of digitization in energy enterprises deepens, it helps establish a more efficient energy production mechanism platform, promoting continuous upgrades and optimization of the energy production process, and achieving a deep integration of industrialization and informatization. For example, China's Datang Corporation Limited uses advanced communication technology and software architecture to construct a three-dimensional virtual power plant, achieving aggregation and coordination optimization of geographically dispersed locations. Its intelligent control system monitors the production of electricity in real-time, completing energy storage and reasonable allocation. Based on this, this paper proposes the second research hypothesis:

Hypothesis 2: Digital trade indirectly reduces energy consumption by promoting energy structure transformation.

Digital trade promotes energy investment and expands energy export demand, thereby inhibiting energy consumption. Final demand comprises consumption, investment, and export within an economic system of a country or region during a specified period. Energy investment relates to the allocation of basic resources in the energy sector, determining the supply, development, and transformation of the energy industry. In the past, China's economic growth was driven by a "high investment, low consumption" model, leading to significant energy consumption increases due to investment overreach, especially in fixed capital demand. Therefore, adjusting China's energy investment is one way to slow down energy consumption growth. Influenced by China's energy resource endowment characteristics, traditional energy has been the main source of energy supply for the past few decades, but its use has also caused substantial carbon emissions and environmental pollution. Accelerating the transition to clean energy is China's long-term goal. Research shows that long-term investment in the energy sector can promote environmental innovation, where innovation replaces labor and capital investment, increasing the demand for renewable energy and reducing the consumption of non-renewable energy, achieving a transition to renewable resources in the energy structure. Digital trade provides a global information exchange platform for the clean energy industry chain, promoting financing and development cooperation among domestic and international enterprises. Through investments in the clean energy supply chain, digital trade fosters innovation and development in new energy technologies, improves energy use efficiency, reduces energy consumption, and brings multiple benefits for energy structure transformation. On the other hand, digital trade expands energy export demand, reducing the consumption of non-renewable energy. International trade is crucial for China's clean energy development, as the demand for clean energy technology from various countries creates a vast domestic market, making China a global leader in clean technology manufacturing and trade. For example, international trade in solar photovoltaic modules accounts for nearly 60% of global demand, and about half of the solar modules manufactured in China are exported. Therefore, digital trade can further expand energy export demand, driving continuous innovation and optimization of domestic clean energy technology, enhancing China's competitiveness in global clean energy technology manufacturing, promoting clean energy trade exports, and increasing the use of clean energy domestically, facilitating energy structure transformation. Based on this, this paper proposes the third research hypothesis:

Hypothesis 3: Digital trade indirectly reduces energy consumption by promoting changes in final demand.

1.2.3. Heterogeneity analysis of the impact of digital trade on energy consumption

The development of digital trade also depends on the differences in regional digital technology levels and resource endowments. The economic development level and resource endowments of different regions vary, resulting in differing impacts of digital trade on energy consumption reduction. On one hand, due to disparities in regional resource endowments, regions with comparative advantages in digital technology resources can develop digital trade more rapidly, thereby reducing local energy consumption and achieving sustainable development. On the other hand, due to economic development level differences among regions, more developed areas tend to shift high-energy-consuming and high-pollution manufacturing industries to less economically developed regions, leading to higher energy consumption in economically lagging areas. Moreover, as digitalization deepens, the gap between regions with strong digital technology resources and those that are less advanced widens, exacerbating the digital divide and intensifying competition for talent and technology, resulting in a siphon effect that manifests the negative externalities of digital trade. The more severe the imbalance in factor allocation, the higher the energy consumption in manufacturing will be. Regional economic, resource, talent, and digital technology levels are crucial factors in the effectiveness of digital trade in reducing energy consumption. Based on this, this paper proposes the fourth research hypothesis:

Hypothesis 4: The inhibitory effect of digital trade on energy consumption is heterogeneous.

2. Methods

2.1. Model specification

2.1.1. Two-way fixed effects model

Based on the theoretical analysis above, it can be seen that the higher the level of digital trade development, the lower the per capita energy consumption. The following two-way fixed effects model is constructed:

$$EC_{it} = \gamma_0 + \gamma_1 DT_{it} + \delta K_{it} + \varphi_i + \tau_t + \varepsilon_{it} \tag{1}$$

In model 1, where *EC* stands for per capita energy consumption; *DT* represents the level of development of digital trade; γ_0 is a constant term; γ_1 is the estimation coefficient of the core explanatory variable, which is expected in this paper according to the previous theoretical analysis $\gamma_1 < 0$; α_i、τ_t、and ε_{it}, are individual effects, time effects, and random disturbance terms, respectively; *K* indicates a set of control variables; and δ is their estimated coefficients. This paper is mainly concerned with the estimated coefficient and significance of the core explanatory variable *DT*.

2.1.2. Mediation model

The baseline regression results show that digital trade can reduce energy consumption, playing an inhibitory role, and the model has passed various robustness tests. Next, we delve into the pathways through which digital trade reduces energy consumption and empirically test the mediating effects of each pathway. The following mediating model analyzes the mediating effects of energy structure transformation and technological innovation:

$$M_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha K_{it} + \varphi_i + \tau_t + \varepsilon_{it} \tag{2}$$

$$EC_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 M_{it} + \beta K_{it} + \varphi_i + \tau_t + \varepsilon_{it} \tag{3}$$

In this case, model 2 explores the effect of DT on intermediary variables, while model 3 explores the effect of DT and intermediary variables on EC. Among them, M_{it} represents the intermediary variables, including two variables: Energy structure transition (ECS) and technological innovation (TC). According to the mediating effect model test method, if α_1 and β_2 significant, the mediating effect exists. If β_2 at least one α_1 of and is not significant, the Bootstrap method is used $\alpha_1 * \beta_1$. In addition, if α_1 and β_2 significant, but γ_1 not significant, it is fully mediated; If γ_1 is significant, and γ_1 has the same sign as $\alpha_1 * \beta_1$, it is a partial mediating effect; If γ_1 is significant, $\alpha_1 * \beta_1$ has the opposite sign to γ_1, it is a masking.

2.2. Variable selection

2.2.1. Dependent variable

Given that absolute energy consumption totals cannot accurately reflect the intensity of energy consumption in various regions, this paper uses per capita energy consumption, defined as total regional energy consumption divided by the total regional population, measured in tons per ten thousand people. The per capita energy consumption data (from the "China Energy Statistical Yearbook") includes coal consumption as the sum of seven related energy terminal consumptions and total energy consumption as the sum of twenty related energy terminal consumptions.

2.2.2. Independent variable

The level of digital trade development (DT). Referencing Pei Guifen's 0 indicator selection method, this paper constructs a measurement system for the level of digital trade development from five dimensions: technical infrastructure, digital technology level, digital trade capacity, digital trade objects, and trade potential, and refines each dimension. Principal component analysis is used to calculate the level of digital trade development in Chinese provinces from 2014 to 2022. Specific indicator system can be found in Table 1.

Table 1. Digital trade development indicator system.

Primary indicators	Secondary indicators	Tertiary indicators
Infrastructure	Internet environment	The total number of domain names
		Number of Internet broadband access ports
		The length of the long-distance optical fiber cables
		Broadband Internet subscriber rate
		Mobile phone penetration rate
	Logistical environment	Per capita courier volume
		Employment density of postal workers
		Freight density
Digital technology	Talent investment	Number of employees in the information software industry
	Technological innovation	Number of patent applications
		R&D expenditure of industrial enterprises above designated size
Digital trade capacity	Digitization of elements	Mobile Internet access traffic
	Digitalization of processes	Number of computers used per 100 people in a business
		Enterprise website ownership rate
		Proportion of enterprises carrying out e-commerce
Digital trade objects	Industrial digital trade	E-commerce sales
		E-commerce purchases
	Digital industrialized trade	Total telecommunications services
		Software business revenue
Trade development potential	Economic strength	GDP per capita
		Per capita living consumption expenditure of residents
	Large-scale trade	Total retail sales of consumer goods

2.2.3. Control variables

Referring to the research results of existing scholars and considering the research needs of this paper, the control variables selected are as follows:

Economic development level (lnGDP): Measured by the per capita GDP of the region, logarithmically transformed. At the initial stage of social development, the higher economic development level, the faster the social development, leading to higher energy consumption intensity, thereby increasing energy consumption.

Foreign direct investment (FDI): Represented by the ratio of regional foreign direct investment (in millions of dollars) to GDP as a proxy variable for foreign direct investment.

Urbanization level (urban): Represented by the proportion of the urban population to the total population at the end of the year. With the advancement of urbanization, energy consumption for urban living and various productions during the urbanization process increases accordingly.

Energy price change (price): Measured by the fuel price index in the commodity retail price index of each region (previous year = 100). Studies indicate that the larger the increase in energy prices, the more effective the reduction in energy consumption intensity through technological innovation 0.

Financial development level (FIN): Measured by the ratio of the balance of deposits and loans of financial institutions to GDP. Literature suggests that digital inclusive finance can improve corporate production efficiency by influencing corporate financing channels and altering corporate economic behavior, thereby reducing corporate energy consumption 0.

Human capital (HR): Represented by the average years of education per capita in the region as a proxy variable for human capital. Higher levels of human capital correlate with higher population quality, which can improve enterprise productivity through a demographic dividend, reducing per capita energy consumption.

Foreign trade level (FT): Measured by the ratio of regional total import and export trade to GDP as a proxy variable for the level of foreign trade.

2.2.4. Mediator variables

Energy structure transformation (ECS): Referencing the approach of Zhang Baofeng 0, this paper selects the proportion of natural gas consumption to total energy consumption as a proxy variable for China's energy consumption structure transformation.

Final demand change (ES): Represented by the energy consumption structure, specifically the proportion of coal consumption to total energy consumption, and logarithmically processed.

2.3. Data sources

Due to data availability, this study selects panel data from 30 Chinese provinces (excluding Hong Kong, Macau, Taiwan, and Tibet) from 2014 to 2022 for analysis. The data mainly come from the "China Statistical Yearbook", "China Energy Statistical Yearbook," and provincial "Statistical Yearbooks". Some energy data sourced from the CEADs China Carbon Accounting Database "Provincial Energy Inventory" [0–0]. All data are annual.

3. Results

3.1. Baseline regression results

To explore the impact of digital trade on per capita energy consumption in China, we first conduct a baseline regression analysis of model 1, and the results are shown in Table 2. Due to the Hausman test result with a p-value of 0.0002, and the F-test passing after adding time dummy variables in the individual fixed effects model, a two-way fixed effects model is used for analysis. Model 1 shows the regression results without control variables, and Models 2–4 show the regression results after gradually adding control variables, time effects, and individual effects. Model 4, which includes control variables and fixes both individual and time effects, indicates that the coefficient of digital trade is −0.0498151 and is significant at the 5% level. This indicating that a 1% increase in the level of digital trade development can reduce per capita energy consumption by 4.9%, thus confirming Hypothesis 1.

Table 2. Baseline regression results.

Model	1	2	3	4
Variables	EC	EC	EC	EC
DT	−0.0424466*	−0.0673725**	−0.0734725***	−0.0498151**
	(−1.73)	(−2.57)	(−4.98)	(−2.30)
LNCGDP		0.0057324	0.0458224	−0.0255647
		(0.06)	(0.94)	(−0.27)
FDI		−0.4918811	−0.5666107	0.0516569
		(−0.87)	(−1.20)	(−0.09)
Urban		1.349325***	1.382979***	0.4634471
		(3.55)	(8.00)	(0.78)
Price		0.0924848***	0.0894577**	−0.0541573
		(3.11)	(2.13)	(−0.28)
FIN		−0.0568057	−0.047767***	−0.0674595*
		(−1.67)	(−3.31)	(−1.84)
HR		0.0626507**	0.0539696**	−0.0028843
		(2.41)	(2.42)	(−0.12)
Open		−0.0521155	−0.0370025	−0.0122532
		(−1.18)	(−0.98)	(−0.30)
Constant	10.48483	8.802071	8.467829	10.89002
	(2153.60)	(11.51)	(18.34)	(10.06)
Time	No	No	No	Yes
Individual	No	Yes	No	Yes
N	270	270	270	270
R^2	0.0123	0.6159	0.6143	0.6730

*p < 10%, **p < 5%, ***p < 1%, the same below.

3.2. Robustness test

To verify the stability of the structure, this paper adopts the following robustness tests.

3.2.1. Replace core explanatory variables

Using the entropy weight method to replace the principal component analysis to calculate the level of digital trade development, and using the mixed regression model, the results are shown in Model 5 of Table 3. After re-regression, the coefficient of digital trade remains negative, proving the reliability of the conclusion.

3.2.2. Endogeneity test

This paper uses the first and second lags of the digital trade index as its current instrumental variables for two-stage least squares regression (2SLS), with the results shown in Models 6 and 7. The data show that the sign and significance of the digital trade coefficient remain unchanged, consistent with the baseline regression results. Additionally, the weak instrumental variable test for the selected instrumental variables has an F value greater than 10, indicating that the weak instrumental variable test is significant and the selected instrumental variables are highly correlated with endogenous variables, proving them strong instruments. The over-identification test (exogeneity test) of the instrumental variables shows the p-value greater than 0.05, indicating that the selected instrumental variables are exogenous and not correlated with the random disturbance term.

Table 3. Robustness test.

Model	5 Entropy weight	6 One period lag as instrumental variable	7 Lag two as an instrumental variable	8 Excluding municipalities	9 Truncation processing
Variables	LNEC	EC	EC	EC	EC
lnDT	−0.1825933*** (−4.10)				−0.0502454** (−2.11)
DT				−0.0947927*** (−4.75)	
L.DT		−0.1030645*** (−7.20)			
L2.DT			−0.0980007*** (−6.38)		
LNGDP	0.5034703** (2.15)	0.552042*** (4.84)	0.5262867*** (4.29)	−0.0201453 (−0.36)	−0.0200157 (−0.22)
FDI	−11.2454** (−2.65)	−12.79069*** (−6.11)	−13.73041*** (−5.73)	−1.090649* (−1.93)	−0.279458 (−0.55)
Urban	3.984811*** (3.59)	3.131112*** (6.33)	3.351852*** (6.11)	1.534994*** (8.12)	0.461222 (0.81)
Price	−0.1279724 (−0.79)	−0.2952998 (−1.31)	−0.1426545 (−0.55)	0.083198* (1.97)	−0.048103 (−0.28)
FIN	−0.091699 (−1.50)	0.0190875 (0.71)	0.0142729 (0.48)	−0.0806912*** (−4.98)	−0.057301* (−1.88)
HR	−0.078697 (−0.91)	−0.1515947*** (−3.02)	−0.1445471** (−2.59)	0.0588517** (2.40)	0.0074584 (0.31)
FT	−0.6380009*** (−3.29)	−0.5417229*** (−3.26)	−0.6345303*** (−3.36)	−0.0263612 (−0.60)	−0.0136057 (−0.35)
Constant	7.764735 (4.23)	6.42254 (4.84)	5.786439 (4.01)	9.086372 (17.31)	10.69486 (11.97)
N	270	270	270	270	270
R^2	0.6116	0.5028	0.5026	0.6453	0.6866
Over-identification test p-value		7350.46			
		0.2158	0.2253		

3.2.3. Excluding municipalities

Due to significant differences between municipalities and other cities, this paper excludes Beijing, Shanghai, Tianjin, and Chongqing for re-regression, with results shown in Model 8. The regression results remain consistent, proving the reliability of the conclusion.

3.2.4. Truncation processing

In regression analysis, if there are outliers in the data, they may significantly influence the regression results, distorting the true results. To eliminate the impact of outliers on the regression results, this paper conducts 1% truncation processing on all variables, with regression results shown in Model 9. The coefficient of digital trade remains significantly negative, proving the conclusion's reliability.

Table 4. Mechanism of action test.

Model	4	10		11	
		Energy structure transformation		Changes in final demand	
Variable	EC	ECS	EC	ES	EC
LNDT	−0.0498151** (−2.30)	0.023144* (2.02)	−0.0385436* (−2.05)	−0.0339236** (−2.3)	−0.0385436* (−2.05)
ECS			−0.4870149* (−1.81)		
ES					−0.4870149* (−1.81)
Controls	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Individual	Yes	Yes	Yes	Yes	Yes
N	270	270	270	270	270
R^2	0.6730	0.3274	0.6819	0.5521	0.6819

3.3. Mechanism of action analysis

The results are shown in Table 4. The results show: Model 10 is the result of taking energy structure transformation as a mediating variable. The regression coefficient between energy structure transformation and digital trade is positive and significant at the 1% level, indicating that digital trade can promote energy structure transformation. After adding the mediating variable, the coefficient of energy structure transformation is significant, and the inhibitory effect of digital trade on energy consumption is weakened, indicating that digital trade reduces energy consumption by promoting energy structure transformation, confirming Hypothesis 2. Model 11 shows that the coefficient of digital trade on final demand change is significant at the 5% level, and after adding the mediating variable, the coefficient of final demand change is significant, indicating that digital trade reduces energy consumption by promoting changes in final demand, confirming Hypothesis 3.

3.4. *Heterogeneity analysis*

In recent years, the development level of digital trade in China has shown a steady upward trend, and the difference in the development of digital trade has been decreasing. However, the development of China's regional digital trade is still unbalanced, and some studies have shown [3] that for a long time, the differences in the development of China's regional digital trade mainly come from the regional differences in the eastern, central and western regions, and they are manifested as "east-west>east-central>central-Western" the spatial non-equilibrium distribution. According to the China Digital Trade Development Report (2022), the development level of digital trade in the eastern region is relatively high, because the eastern region usually has more advanced digital infrastructure, technology and talents, and the eastern region has a higher level of economic development, which can better support and promote the development of digital trade. In the more economically and socially developed regions, the scale of trade in goods and services is larger, and the vitality and growth potential of trade are more significant. At the same time, the application of digital technology in these regions is wider, the digital trade methods are more flexible and diverse, and the development level of digital trade is relatively higher. The development level of digital trade in the central region is relatively lagging behind, but in recent years, with the support of national policies, the development of the central region has gradually accelerated. The foundation of digital trade in the western region is relatively weak, but the region has advantages such as abundant land and green power resources, low temperature, and low cost of data and computing power centers, showing good potential for the development of digital trade. With the implementation of the "Eastern Data and Western Computing" project, remarkable progress has been made in the construction of digital infrastructure in the western region, laying the foundation for the high-quality development of the regional economy. Therefore, it is necessary to perform a heterogeneity analysis of differences across regions.

Given the limited data set in this paper, when examining the impact of digital trade on regional heterogeneity of energy consumption, the use of grouped regression may result in a smaller number of data points in each group and a less robust model. Therefore, we employ two analytical approaches. First, we utilize the interaction term of adding regional dummy variables and per capita energy consumption. Second, we employ grouped regression to provide supplementary illustration. Furthermore, this paper employs a random effects model to incorporate the interaction term and a fixed effects model in the grouped regression. Regression results are shown in Table 5.

Model 12 uses the interaction terms of regional dummy variables with digital trade. Taking the western region as the benchmark, the estimated coefficients of the digital trade development index in the eastern and central regions are lower than those in the western region, that is, compared with the western region, the inhibitory effect of digital trade on per capita energy consumption is stronger in the eastern and central regions. Models 13–15 are the regression results of the eastern, central, and western regions, respectively. It can be seen that the estimation coefficients of digital trade in the three regions are all negative, indicating that the higher the level of digital trade development in each region, the lower the per capita energy consumption, which further extends hypothesis 1 in the regional direction. Among them, the estimation coefficients of DT in the eastern and central regions are significant at 1% and 10%, respectively, but there are some differences in the absolute values of their estimation coefficients, that is, compared with the central region, the development level of digital trade in the eastern region has a stronger impact on per capita energy consumption. However, the estimation coefficient of digital trade in the western region does not reach the significance level of 10%, so there is no significant correlation between the development level of digital trade and its per capita energy consumption in the western region. Hypothesis 4 is true.

Table 5. Heterogeneity analysis of per capita energy consumption in digital trade.

Model	12 Regional dummy variables vs. DT	13 Eastern region	14 Central region	15 Western region
DT	−0.0234107	−0.154***	−0.0806*	−0.0129
	(−1.28)	(−3.35)	(−1.77)	(−1.09)
East*DT	−0.1850784***			
	(−2.65)			
Center*DT	−0.0615007			
	(−1.06)			
Control variables	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Regional	No	No	No	No
Constants	10.25664	15.71***	3.097	7.560***
	(11.50)	(7.36)	(1.18)	(7.73)
N	270	99	54	50
R^2	0.6868	0.7558	0.7976	0.8784

4. Conclusion

The purpose of this study is to explore the relationship between the development of digital trade and energy consumption. This study constructs an index system of digital trade development and calculates the development level of digital trade by using principal component analysis, and uses per capita energy consumption as a measure for energy consumption. Based on provincial panel data from China spanning from 2014 to 2022, the empirical analysis examines the relationship between the level of digital trade development and per capita energy consumption. The main research findings are as follows:

First, the baseline regression results show that higher levels of digital trade development are associated with lower per capita energy consumption. Furthermore, to ensure the robustness of the model, this paper employs various robustness checks. These included recalculating the level of digital trade development using the entropy weight method to replace the core explanatory variable, using the first and second lags of digital trade as instrumental variables to address endogeneity issues, excluding direct-controlled municipalities, and applying data winsorization. All results indicate that the conclusions of this study are robust.

Second, the analysis of the mechanism reveals that digital trade reduces energy consumption through a mediating effect. This reduction is achieved by promoting the transition of the energy structure and changes in final demand.

Third, the examination of regional heterogeneity found that the impact of digital trade on per capita energy consumption varies across different regions. Compared to the central region, the inhibitory effect of digital trade on per capita energy consumption is stronger in the eastern regions. This difference may be attributed to the resource endowments in the eastern region. The resource endowments in the eastern region have reached a frontier level, where more advanced digital infrastructure, technology, talent, and more efficient lifestyles and production methods provide better support for energy saving and consumption reduction. However, digital trade is not correlated with per capita energy consumption in the western region.

5. Policy proposition

Based on these research conclusions, and to promote the development of digital trade and further reduce energy consumption levels, this paper proposes the following policy recommendations:

First, each province should actively promote the development of digital trade and strengthen its inhibitory effect on energy consumption. Governments can incentivize companies to adopt digital technologies by providing financial subsidies, tax incentives, and other measures, thereby enhancing their efficiency and competitiveness and fostering the growth of e-commerce and other forms of digital trade. By creating digital trade industry clusters and encouraging the agglomerated development of upstream and downstream enterprises in the industrial chain, scale effects can be achieved, further amplifying the role of digital trade in reducing energy consumption. Second, leverage digital trade to facilitate the transformation of the energy structure and changes in energy demand. Traditional enterprises and energy-intensive enterprises should be encouraged to develop and use digital technologies, especially innovative technologies in energy production, distribution and consumption. By using low-carbon, low-pollution renewable and clean energy sources, the energy structure can be steered towards more environmentally friendly development. At the same time, public awareness of climate change and environmental protection should be raised through media, educational systems, and community activities. Advocating for low-carbon and eco-friendly lifestyles in daily life, such as reducing meat consumption, choosing energy-efficient appliances, lowering air conditioning temperatures, and reusing and recycling items, can further support this transition. Third, strengthen inter-provincial cooperation to promote the coordinated development of digital trade across regions. In view of the leading position of the eastern region in digital trade in energy conservation and consumption reduction, the policy should continue to support the development of the digital economy in the eastern region, ensure that its resource endowment is fully utilized, build a characteristic industry of digital trade in the eastern region, and form a demonstration zone for the development of digital trade. At the same time, it will establish cooperation mechanisms with the central and western regions, such as technology sharing and talent exchanges, to promote the dissemination of knowledge and experience, thereby improving the level of digital trade in the central and western regions. For the central region, it is necessary to continue to strengthen the construction of digital infrastructure, vigorously develop the digital economy to address factors constraining the reduction of energy consumption through digital trade. Western region needs to conduct in-depth research on why digital trade is not related to per capita energy consumption in order to formulate more targeted policies.

Use of AI tools declaration

The authors declare they have not used AI tools in the creation of this article.

Acknowledgments

This work was supported by Research Projects of Guangzhou University (YJ2023017) and Major Projects of National Social Science Fund (23&ZD127).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author contributions

Conceptualization, Mengxin Wang and Siyu Zhang; Methodology, Songlan Zhou; Data curation, Leyan Zuo and Songlan Zhou; Writing draft, Siyu Zhang and Leyan Zuo; Review and Editing, Mengxin Wang and Siyu Zhang.

References

1. Weber RH (2010) Digital trade in WTO-law-taking stock and looking ahead. *Asian J WTO Int Heal* 5: 1–24. https://doi.org/10.2139/ssrn.1578139
2. Ma SZ, Chao F, Liang YF (2018) Digital trade: Definition, practical significance and research prospects. *Int Trade* 2018: 16–30. https://doi.org/10.13510/j.cnki.jit.2018.10.002
3. Li W, Li T (2023) Study on China's digital trade development and its comprehensive evaluation in provincial level—Based on quantitative measurement analysis of digital trade development in Fujian province. *Price: Theory Pract* 2023: 171–175. https://doi.org/10.19851/j.cnki.CN11-1010/F.2023.12.469
4. Zhang YF, Li QY (2024) Measurement of China's digital trade development level and dynamic evolution analysis. *Commer Econ* 2024: 126–130. Available from: https://kns.cnki.net/kcms2/article/abstract?v=k15566fjT2kic5JHCkriIQ7dml8zzR1C3CpBw7gItv4RLemdElxTzNFinubJyjbwCiusih-qljLi7tU292xhosaQNsek9B_xF8k6oxjHXs-Ivb8dCjw9ZzFdZ9rJ1S_hiLDt4P_e34IBh9oSJPYKMpsCVJuFKBFAE7_LW1uiOh3IK1sK0GTVfy20sEIv_qPzKMhrYlyAl0w.
5. Pei GF, Liu Y (2024) The impact of digital trade development on industrial structure upgrading in China: An empirical study based on the Spatial Dubin Model. *Stat Decis* 2024: 162–166. https://doi.org/10.13546/j.cnki.tjyjc.2024.06.029
6. Shen B, Li X (2020) Financial development, industrial structure upgrading and energy efficiency improvement. *Inq Econ Issues* 41: 131–138. Available from: http://www.jjwtts.com/CN/Y2020/V41/I12/131.

7. Zou GN, Huang JQ, Zhang WC (2023) Can environmental taxes reduce China's energy consumption? *Econ Theory Bus Manag* 43: 95–105. Available from: http://jjll.ruc.edu.cn/CN/Y2023/V43/I6/95.
8. Wang J, Zheng HY, Zhang YJ (2021) How does trade liberalization affect energy consumption?—From the perspective of energy-saving technological progress. *Zhejiang Acad J* 2021: 108–116. https://doi.org/10.16235/j.cnki.33-1005/c.2021.03.012
9. Lang CL (2012) Empirical research on influence factors of energy consumption in China—Based on different input and output index of technological innovation. *Sci Technol Manag Res* 32: 60–67. https://doi.org/10.3969/j.issn.1000-7695.2012.17.013
10. Hou GS, Hou Y (2021) An empirical analysis of the relationship between environmental regulation, technological innovation and energy consumption. *Sci Technol Manag Res* 41: 216–223. https://doi.org/10.3969/j.issn.1000-7695.2021.20.026
11. Fu ZH, Jing PQ (2022) Local government governance capability, industrial structure transformation, and energy consumption. *Stat Decis* 38: 162–166. https://doi.org/10.13546/j.cnki.tjyjc.2022.10.032
12. Li BZ, Cai YQ (2021) Measurement of the impact of manufacturing servitization transformation on energy consumption levels—An empirical analysis based on panel data of 39 industries in China. *Southeast Acad Res* 2021: 159–169. https://doi.org/10.13658/j.cnki.sar.2021.05.017
13. Zhao TT, Xu MB, Qin LG (2023) Research on the impact of green finance on energy consumption structure. *J Tech Econ Manag* 2023: 55–59. Available from: https://lib.cqvip.com/Qikan/Article/Detail?id=7110928765&from=Qikan_Search_Index.
14. Sun F, Liu Y, Sun CL (2024) The impact mechanism of digital empowerment on low–carbon transformation of traditional energy industries. *Sci Technol Manag Res* 44: 172–180. Available from: http://kjglyj.ijournals.cn/kjglyj/article/abstract/20230603018.
15. Xie HQ, Yang Q, Wu XD (2023) Study on the impact of digital trade on China's regional carbon emission reduction. *Price: Theory Pract* 2023: 180–184. https://doi.org/10.19851/j.cnki.CN11-1010/F.2023.11.448
16. Wen CJ (2024) Mechanism analysis of the impact of digital trade on the green efficiency of China's logistics industry. *J Commer Econ* 2024: 130–134. Available from: https://kns.cnki.net/kcms2/article/abstract?v=k15566fjT2l2pcrVxHu_0nZxqpfh_yzQ6OzpikhlKVdIdCgwdrJsKrYiNqw_2p1Mn4gBF3sd4nUMfohWKQ4LwdVfGsTPfIStBYXWFgGCZO1znovJpmlO3TGF9BpeCz2P5dzBhEMmOfUNgE8Myd51juMk_NV3N5Tg6GrXM5bDnbE36Xyp3L3dkPylw2345gK7S-e8iYDMnLg.
17. Bie F, Yang Y, Shen H, et al. (2024) Inclusive digital economy, resource dependence and changes in the urban energy mix: City level analysis from China. Resour Policy 92: 105027. https://doi.org/10.1016/j.resourpol.2024.105027
18. Liu X, Qin C, Liu B, et al. (2024) The economic and environmental dividends of the digital development strategy: Evidence from Chinese cities. J *Clean Prod* 440: 140398. https://doi.org/10.1016/j.jclepro.2023.140398
19. Zhu Y, Lu S (2024) Digital economy and carbon neutrality: Exploring the pathways and implications for China's sustainable development. *J Knowl Econ* 2024: 1–18. https://doi.org/10.1007/s13132-024-01931-y

20. Wang L, Zan L (2024) The impact mechanism and spatial effect of digital financial inclusion on energy-environmental efficiency. *J Stat Inform* 39: 45–59. Available from: https://link.cnki.net/urlid/61.1421.c.20240529.1527.004.
21. Zhang BF, Cai LM (2024) The impact of digital economy on the transformation of energy structure: Theoretical mechanism and empirical test. *J China Univ Min Technol* 26: 153–168. https://doi.org/10.20089/j.cnki.issn.1009-105x.2024.01.013
22. Xu J, Guan Y, Oldfield J, et al. (2024) China carbon emission accounts 2020–2021. *Appl Energy* 360: 122837. https://doi.org/10.1016/j.apenergy.2024.122837
23. Guan Y, Shan Y, Huang Q, et al. (2021) Assessment to China's recent emission pattern shifts. *Earths Future* 9: e2021EF002241. https://doi.org/10.1029/2021EF002241
24. Shan Y, Huang Q, Guan D, et al. (2020) China CO_2 emission accounts 2016–2017. *Sci Data* 7: 54. https://doi.org/10.1038/s41597-020-0393-y
25. Shan Y, Guan D, Zheng H, et al. (2018) China CO_2 emission accounts 1997–2015. *Sci Data* 5: 1–14. https://doi.org/10.1038/sdata.2017.201
26. Shan Y, Liu J, Liu Z, et al. (2016) New provincial CO_2 emission inventories in China based on apparent energy consumption data and updated emission factors. *Appl Energy* 184: 742–750. https://doi.org/10.1016/j.apenergy.2016.03.073