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Digital Dividend or Digital Divide? How the Digital Economy Shapes China's Agri-Food Trade Dynamics: Evidence on Impacts, Mechanisms, and Heterogeneity

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Abstract

Digital economy has profoundly reshaped the global trade landscape, yet its implications for agricultural trade, particularly in major agricultural trading countries, remain relatively underexplored. Using provincial panel data from China covering the period from 2013 to 2023, this study investigates whether digital economy development in China's agricultural trade generates a digital dividend or instead exacerbates a digital divide. We construct a unified analytical framework and employ two-way fixed-effects models to identify the effects and underlying mechanisms. The results indicate that digital economy development significantly enhances overall agricultural trade performance. Mechanism analyses further show that this effect operates primarily through improvements in agricultural total factor productivity and the upgrading of rural human capital. Notably, the trade-enhancing effects of the digital economy exhibit pronounced regional heterogeneity. These effects are concentrated mainly in eastern and northern regions and are substantially stronger in non-grain-producing areas, while remaining statistically insignificant in central and western regions. This study contributes to the literature by providing a regionally differentiated assessment of the relationship between the digital economy and agricultural trade. It also offers policy implications for narrowing the digital divide through coordinated investments in digital infrastructure, productivity enhancement, and human capital accumulation.

Keywords: digital economy; agri-food trade dynamics; agricultural trade performance; trade competitiveness; total factor productivity; rural human capital

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1. Introduction

The evolution of modern information technologies has fundamentally reshaped the global economic landscape [1–3]. Digital technologies are profoundly changing production modes, trading patterns, and industrial organization in international trade [4,5]. The scale of China's digital economy has expanded from approximately USD 1.58 trillion in 2012 to USD 7.59 trillion in 2023, representing a 3.8-fold increase over 11 years, ranking among the highest globally [6]. At the same time, agricultural imports and exports also occupy an important position in China's economy [7,8]. Overall, China's agricultural trade remains at a high level, showing a structural trend of steady export growth and a narrowing trade deficit [9,10]. The total import and export volume in 2024 reached USD 318.16 billion, a slight year-on-year decrease of 4.3%, while remaining historically high level. From January

to August 2025, the total agricultural trade volume was USD 201.71 billion, of which exports made up USD 65.81 billion, while imports totaled USD 135.90 billion. Consequently, the agricultural trade deficit stood at USD 70.09 billion, marking a 14.0% decline compared to the same period of the previous year.

In the agricultural field, the digital economy, with its strong integration capacity, low marginal cost, and platform-based ecosystem advantages [11,12], is profoundly reshaping China's agricultural economic system. Through technologies such as digital cold chains and satellite remote sensing, digital technologies enhance efficiency, reduce circulation costs, lower trade barriers, and strengthen linkages between smallholders, firms, and international markets [13,14]. In 2020, against the background of the global spread of the new crown pneumonia epidemic, our country's agricultural product cross-border e-commerce achieved contrarian growth in the same period, with total retail imports and exports of USD 6.34 billion, a year-on-year increase of 19.8%. In 2024, The scale of China's cross-border e-commerce import and export of agricultural products exceeded USD 11 billion, accounting for 12.3% of the total agricultural trade volume. As a result, the digital economy has increasingly functioned as a "driver" for China's agricultural import–export activities. This raises several important questions: To what extent does digital-economic progress elevate China's agricultural trade performance? Through which mechanisms does this influence operate? And under varying regional conditions, resource endowments, and industrial structures, do these effects manifest differently? Addressing these issues not only advances theoretical understanding of how the digital economy empowers agricultural trade, but also contributes to the development of new analytical perspectives within digital-era trade theory, offering practical relevance for fostering China's high-quality and sustainable agricultural trade development.

A growing body of literature has examined how the digital economy reshapes agricultural production, circulation, and trade. One major strand of research focuses on trade cost reduction, arguing that digital technologies lower information, communication, transaction, payment, logistics, and institutional barriers through technological empowerment and disintermediation, thereby facilitating agricultural trade [15–17]. However, some studies also note that such positive effects depend on whether digitalization can sufficiently offset traditional trade frictions such as tariffs and transportation costs [18–20]. Another related line of research emphasizes the role of the digital economy in improving agricultural production efficiency. Existing studies generally suggest that digital technologies enhance agricultural productivity through technological innovation, factor integration, and data-driven decision-making, which in turn strengthens the competitiveness of agricultural products in international markets [21–25].

Another strand of the literature examines how the digital economy reshapes agricultural trade patterns by transforming trading modes and expanding market access. Digital platforms leverage big data, cloud computing, and intelligent matching technologies to overcome traditional barriers related to geographical distance, cultural differences, and intermediary constraints, thereby reducing transaction costs and lowering market entry thresholds [26–30]. In particular, cross-border e-commerce platforms enable small-scale operators and micro-enterprises to directly participate in international trade through long-tail effects and precision matching mechanisms, transforming fragmented demand for niche agricultural products into scalable market opportunities [31–33]. Moreover, digital trade networks improve real-time matching between supply and demand and enhance resource allocation efficiency, contributing to higher transaction efficiency and stronger market competitiveness [34,35]. Consequently, the digital economy not only broadens the range of participating trade entities and spatial scope of agricultural trade but also

promotes its sustainable growth and structural upgrading through demand expansion and competitive effects [36,37].

Despite these valuable contributions, several gaps remain in the existing literature. First, many studies rely primarily on national-level analyses, paying limited attention to regional disparities in digital economy development. Second, existing research often focuses exclusively on either agricultural exports or imports, resulting in a fragmented understanding of agricultural trade dynamics. Third, heterogeneity analyses tend to emphasize product categories or trade modes, while differences in regional strategic positioning and agricultural development orientation, particularly under food security considerations, are relatively underexplored. Therefore, we adopt a unified analytical framework to jointly examine agricultural imports and exports and systematically investigate the mechanisms and regional heterogeneity of digital economy effects on China's agricultural trade.

This paper aims to systematically examine how digital economy development affects China's agricultural trade performance and to identify the underlying mechanisms through which digitalization operates, particularly via improvements in production efficiency and human capital accumulation. There are at least two reasons why conducting such empirical research in the Chinese context is of both theoretical and practical importance. First, China simultaneously engages in substantial agricultural imports and exports, with pronounced structural differences across regions. Clear regional variations in trade orientation, product composition, and market participation make China an ideal case for assessing whether the digital economy facilitates agricultural trade upgrading or instead amplifies regional disparities. Second, although China's digital economy has expanded rapidly, its development remains highly uneven. This uneven development provides a unique institutional and practical setting for identifying the heterogeneous effects of the digital economy on agricultural trade. By focusing on the complex and representative case of China, this study not only clarifies the key mechanisms through which digital economy development influences agricultural trade but also offers more nuanced empirical evidence on the structural characteristics of agricultural trade transformation in the context of digitalization.

We make three main contributions. First, using provincial panel data, we systematically assess regional heterogeneity in the relationship between digital economy development and China's agricultural trade, which extends the literature from macro-level analyses to a more nuanced regional perspective. Second, the study treats agricultural imports and exports within a unified analytical framework, thereby revealing the dual function of the digital economy in enhancing export capacity and facilitating import optimization. This approach enables a more comprehensive understanding of how digital empowerment shapes the evolution of China's agricultural foreign trade. Third, the paper incorporates agricultural total factor productivity(TFP) and rural human capital as mediating variables and systematically identifies the channels through which the digital economy influences agricultural trade—namely through improved factor allocation, efficiency gains, and knowledge spillovers. The results further indicate that the magnitude and direction of these effects differ across regions and industrial contexts, providing empirical evidence that supports the development of precise, region-specific digital trade strategies at the national level.

2. Development Status of China's Digital Economy and Agricultural Trade

2.1. Measurement and Dynamic Evolution of the Digital Economy

Referring to the studies of He et al. [38] and Liu et al. [39], we construct an index to evaluate the digital economy in China (Table 1). Furthermore, based on this framework, the entropy method is employed to measure the status of the digital economy and to calculate

the levels of digital economy development from 2013 to 2023. This approach captures the dynamic evolution of China's digital economy over the past decade, as illustrated in Figure 1. It should be noted that the digital economy is a multidimensional concept, and no single indicator system can fully capture all of its components. The index constructed in this study focuses on the overall level of digital economy development at the regional level, rather than sector-specific digital applications.

Table 1. Indicator system for digital economy.

Primary Indicator	Secondary Indicator	Tertiary Indicator
Level of Digital Economy	Digital Infrastructure	Internet broadband access rate
		Internet broadband penetration rate
		Scale of mobile communication facilities
		Length of long-distance optical cable lines
		Number of web pages
		Number of domain names
	Digital Industrialization	Per capita volume of telecommunication services
		Mobile phone rate
		Number of IT service industries
		Proportion of employees in the information and software industry
		Number of authorized domestic patent applications
		Number of accepted domestic patent applications
	Industrial Digitalization	Digital inclusive finance index
		Proportion of enterprises engaged in e-commerce activities
		Total e-commerce sales
		Number of websites per 100 enterprises
		Added value of secondary and tertiary industries
		Investment in science and technology innovation
		Volume of express deliveries

According to Figure 1, China's digital economy remains at a moderate stage, showing a generally positive growth trend and promising prospects. From 2013 to 2020, both the national and regional digital economy indices exhibited steady and continuous growth, marking rapid expansion in China's digital economy. The fastest growth occurred between 2018 and 2020, when the national average index surged from 0.131 in 2017 to 0.216 in 2020. During this period, strong government policy support—such as the "Internet Plus" initiative, the Digital China strategy, and breakthroughs in emerging technologies including 5G, artificial intelligence, and blockchain—greatly accelerated the processes of industrial digitalization and digital industrialization. However, in 2021, the digital economy indices of all regions (eastern, central, and western) declined for the first time, with the national average index falling by approximately 13.2%. Although there was a partial rebound in 2022, the index dropped again in 2023, likely due to weakening market demand, slower global economic growth, and rising trade protectionism.

From a regional perspective, China's digital economy exhibits a distinct east–west disparity, indicating a clear imbalance in regional development that warrants greater attention. Specifically, the eastern region consistently leads the country, with its digital economy index remaining well above the national average. In 2023, the eastern region's index reached 0.276, about 50% higher than the national average, reflecting its strong advantages in infrastructure, talent, technology, and investment. In contrast, the central and western regions remain at relatively lower levels, with the central region positioned between the two and the western region ranking lowest. Nevertheless, both regions maintained steady upward trends. From 2013 to 2020, the index in the western region grew

by approximately 2.61 times, and in the central region by 2.45 times, both outpacing the 1.57-fold increase in the east. It is noteworthy that China's "digital divide" is transitioning from a phase of rapid expansion to one of relative convergence. The central and western regions are closing the gap with the east at an accelerated pace.

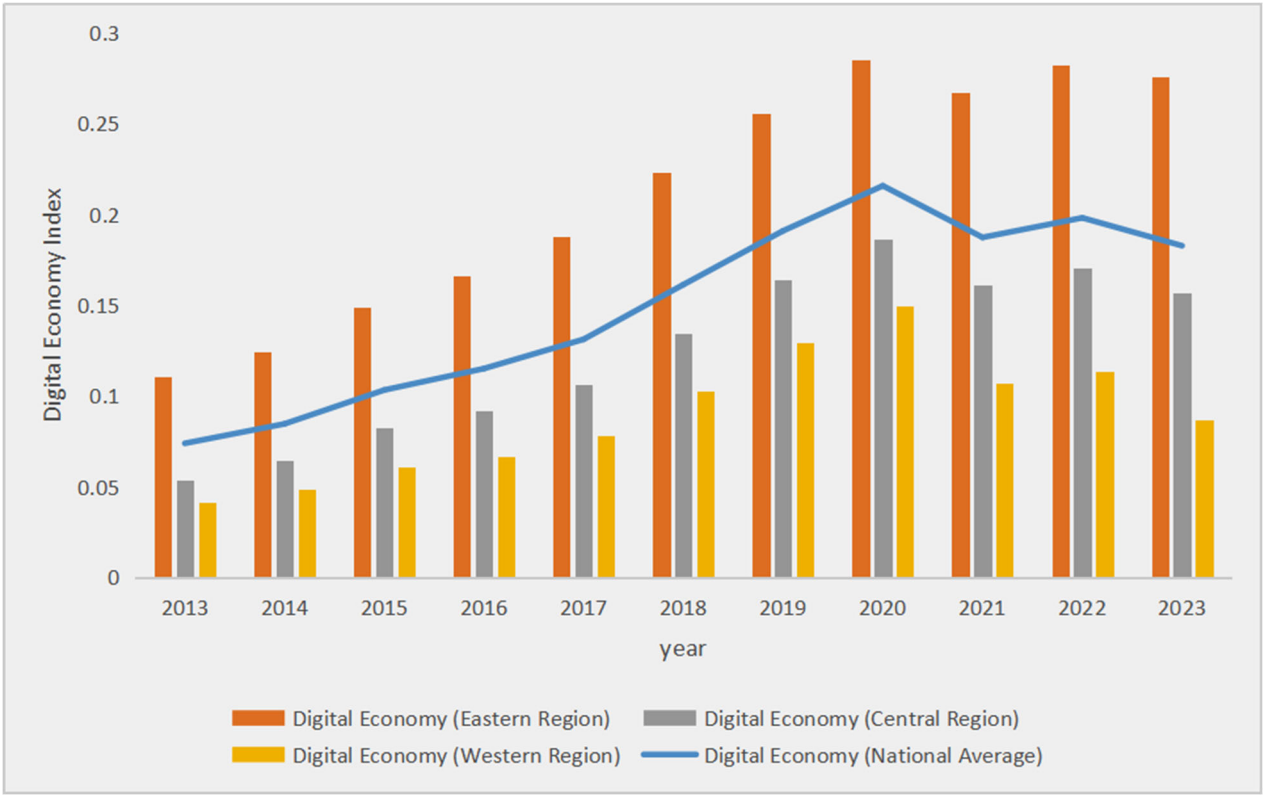

Figure 1. Digital economy in China from 2013 to 2023. Source: Our calculations.

2.2. Current Situation of Agricultural Trade Development

From 2013 to 2023, China's agricultural import and export trade was characterized by import dominance and an expanding trade deficit (Figure 2). During this decade, the import value of agricultural products remained significantly higher than the export value, and the growth rate of imports exceeded that of exports, leading to a continuously widening gap between the two. Specifically, the import value of agricultural products increased sharply from approximately USD 37 hundred million in 2013 to about USD 84 hundred million in 2023. Over the same period, agricultural exports rose more moderately, from around USD 21.3 hundred million to approximately USD 35.7 hundred million, an increase of about 68%. As a result, China's agricultural trade deficit expanded substantially, from approximately USD 16.4 hundred million in 2013 to nearly USD 48.8 hundred million in 2023.

The strong growth in agricultural imports, particularly the sharp rise after 2018, reflects structural demand pressures stemming from China's large population, rising consumption levels, food security requirements, and deeper integration into global agricultural supply chains. On the other hand, the steady yet relatively slow increase in agricultural exports reflects China's comparative advantage structure in the international market. China has maintained advantages mainly in labor-intensive products such as vegetables, fruits, and aquatic products. However, with the intensification of international competition, the rise of trade barriers, and the increase in domestic production costs, China's agricultural exports have encountered growing challenges in recent years. The accelerated yet moderate growth in exports indicates that China must further develop new drivers of agricultural

productivity by enhancing production efficiency, product quality, and brand value to tap into the potential of emerging global agricultural markets.

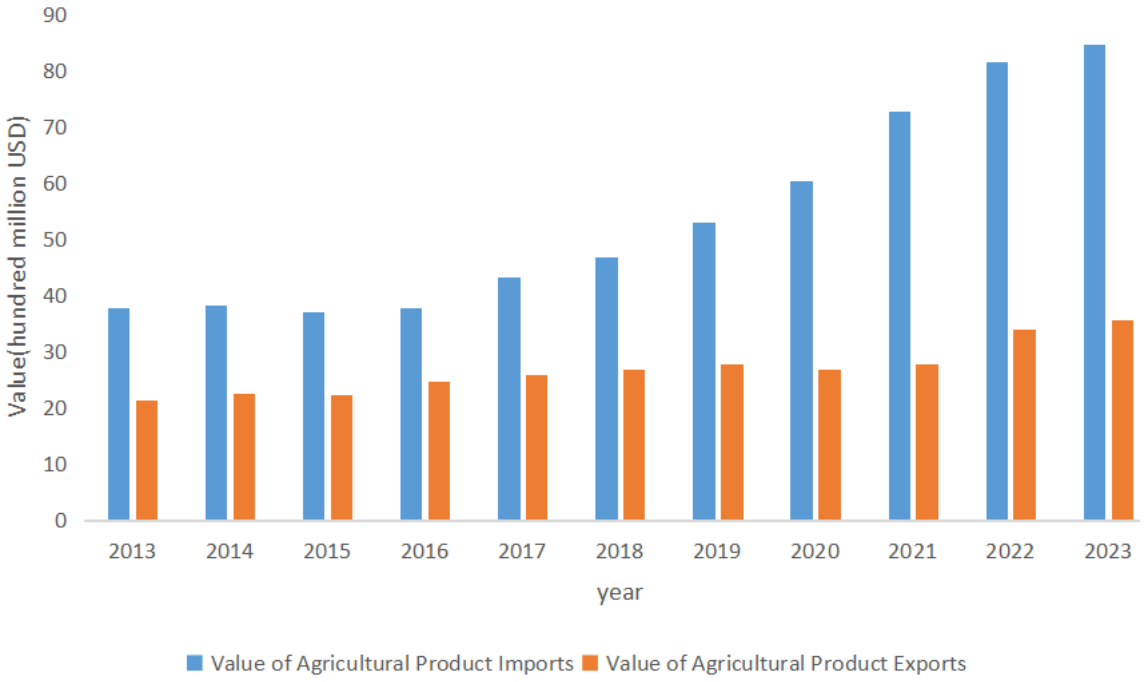

Figure 2. Agricultural import and export trade volume in China from 2013 to 2023. Source: National Bureau of Statistics of China.

3. Theoretical Analysis and Research Hypotheses

3.1. Impact of Digital Economy on China's Agricultural Trade Level

Emerging digital economy models, such as live-streaming commerce, directly link agricultural producers with consumers, expanding market demand and accelerating the transformation of traditional production modes. This enhances agricultural production efficiency and product quality. Meanwhile, by shortening complex intermediary trading links, the digital economy helps overcome the "stranger effect" caused by geographical distance and linguistic and cultural barriers, thereby reducing time, information, communication, and negotiation costs. These improvements reduce commodity costs, increase product competitiveness, and expand the scale of agricultural imports and exports [40,41]. At present, a growing body of literature has empirically shown that the development of the digital economy, particularly cross-border e-commerce, promotes international trade by reducing transaction costs, improving governance efficiency, and facilitating cross-border transactions [42–44]. Based on this reasoning, the following hypotheses are proposed:

H1. *The development of the digital economy can directly promote the improvement of China's agricultural trade level.*

3.2. Mechanisms of the Impact of Digital Economy on China's Agricultural Trade Level

First, the digital economy promotes agricultural trade through the improvements of agricultural TFP. The quality of both import-substitute and export-oriented agricultural products are strengthened, ultimately influencing the overall level of agricultural trade. Chen et al. [45] argue that the development of agricultural digitalization has transformed traditional agricultural production, machinery, industrial, and input systems. Digital information enables low-cost resource allocation, promoting intelligent, precise, and large-scale

agricultural production and improving production efficiency. Higher the agricultural productivity of a country or region, the stronger its international competitiveness in agricultural products, and consequently, the greater its impact on import and export trade [46,47].

Second, human capital effect also plays a critical role. Digital economy enhances rural human capital by improving farmers' skills in technology adoption, market participation, and trade-related decision-making It strengthens farmers' abilities in technological application, trade participation, and market analysis, thereby influencing the level of agricultural trade [48,49]. Digital agriculture relies on digitally literate rural labor as a foundational input for integrating digital technologies with traditional agricultural practices [50]. Education serves as the guarantee for human capital development. Digital technologies have profoundly transformed the structure and content of educational institutions, improving and extending internal relations within education systems, which in turn promotes the enhancement of human capital [51]. Based on this reasoning, the following hypotheses are proposed:

H2. *The digital economy promotes the level of China's agricultural trade by improving agricultural TFP*.

H3. *The digital economy promotes the level of China's agricultural trade by enhancing rural human capital*.

3.3. Heterogeneity in the Impact of Digital Economy on China's Agricultural Trade Level

China's vast territory and complex geographical environment result in significant differences in natural endowments such as topography, climate conditions, and ecological resources across regions [52,53]. For instance, the eastern coastal areas benefit from convenient transportation networks, a higher degree of informatization, and well-developed industrial chains, while the central and western regions rely more on agricultural resources and labor inputs. These disparities not only lead to varying levels of digital infrastructure development but also cause substantial differences in the paths and efficiency of agricultural digital transformation. Meanwhile, regional disparities in economic development levels, industrial structures, government policy support, technological innovation capacity, and market openness also contribute to variations [54]. Existing studies indicate that digital economy affect agricultural international trade is heterogeneous across different dimensions, such as differences in product types affect the value-added effects of trade; regional differences determine the depth of digital penetration; and variations in trade modes influence the efficiency of cross-border transactions [55]. Therefore, it can be inferred that the impact of digital economy development on China's agricultural import and export trade is not homogeneous but jointly regulated by differences in natural endowments and economic foundations. We proposed following hypotheses:

H4. *The impact of digital economy on China's agricultural trade level exhibits heterogeneity*.

Figure 3 illustrates the theoretical framework of how the digital economy influences China's agricultural trade level.

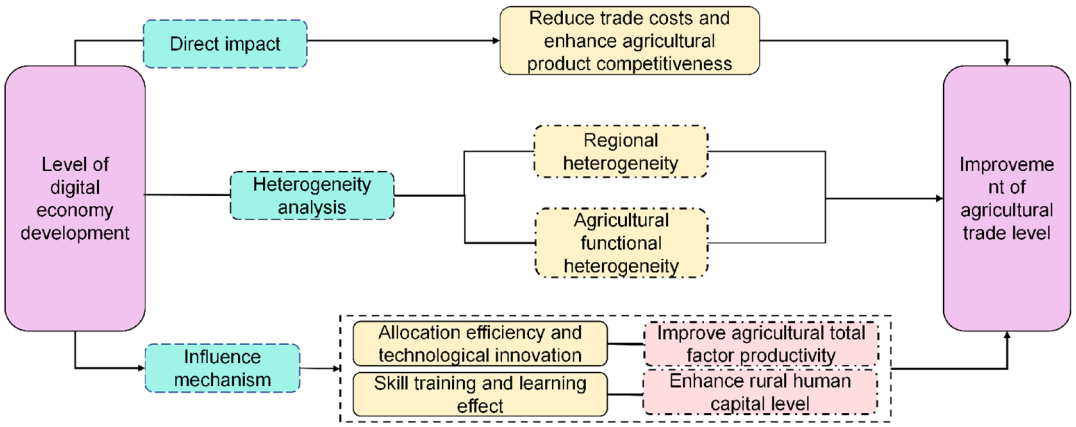

Figure 3. Theoretical framework.

4. Research Design

4.1. Models

This paper constructs a two-way fixed effects benchmark model. The specific form is shown in Equation (1):

$$ATL_{it} = \alpha + \beta_1 Dige_{it} + \gamma \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

ATL_{it} represents the agricultural trade level in China. $Dige_{it}$ represents the level of digital economy. The vector X_{it} represents the control variables, including: total agricultural machinery power, crop planting structure, agricultural disaster rate, proportion of fiscal expenditure on agriculture, agricultural industrial structure, and urbanization rate. μ_i and λ_t represent fixed effects.

This paper constructs the following regression model to test influence mechanisms:

$$M_{it} = \alpha_1 + \beta_2 Dige_{it} + \gamma_1 \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Here, M_{it} represents the two mediating variables, TFP and Human, while the remaining variables are defined as in Equation (1).

4.2. Variable Description

4.2.1. Explained Variable

The core explained variable in this paper, agricultural trade level (ATL), is defined as the ratio of the total value of agricultural imports and exports to total agricultural value in each province. The calculation formula is as follows:

$$ATL_{it} = \frac{Imports_{it} + Exports_{it}}{Agricultural\ Value_{it}} \quad (3)$$

4.2.2. Explanatory Variable

The core explanatory variable in this paper is the digital economy level (Dige). This indicator is calculated from Table 1.

4.2.3. Control Variables

Referring to the studies of Ye et al. [53] and Zhou and Tong [56], control variables are as follows: (1) Total agricultural machinery power (AM): used to describe the level of mechanization and equipment in agricultural production. (2) Crop planting structure (APS): measured by the grain-to-economic crop ratio or the proportion of dominant crops.

(3) Agricultural disaster rate (ADR): represented by the ratio of affected area to the total sown area of cultivated land. (4) Proportion of fiscal expenditure on agriculture (AFP): expressed as the ratio of fiscal expenditure on agriculture to total local fiscal expenditure. (5) Agricultural industrial structure (AIS): represented by the proportion of the total value of the primary industry in regional GDP. (6) Urbanization rate (UR): measured by the proportion of the urban resident population in the total population.

4.2.4. Mechanism Variables

(1) Agricultural Total Factor Productivity (TFP): Referring to Ye et al. [57], this paper uses crop sown area, agricultural employment, total agricultural machinery power, total effective amount of fertilizer applied (in pure form), and effective irrigated area as input variables, while using the agricultural value as the output variable. The EBM-SBM model is applied to measure the growth of agricultural TFP. (2) Human Capital (Human): Human capital is measured by the average years of education of rural residents. This indicator primarily captures the level of general human capital, reflecting cognitive skills, learning capacity, and the ability to absorb and apply new technologies, rather than directly measuring digital literacy or specific digital skills. Following common practice in the literature, average years of schooling is employed as a proxy for human capital.

4.3. Data Sources

This paper takes 30 provinces in China as the research samples. Considering the difficulty of data acquisition, Tibet, Hong Kong, Macao, and Taiwan are excluded. In view of data availability, the study period is 2013–2023. The data mainly come from the China Rural Statistical Yearbook and China Statistical Yearbook. Descriptive of relevant variables is presented in Table 2.

Table 2. Descriptive statistical analysis.

Variable Type	Variable Name	N	Mean S.D.	Std. Dev.	Min.	Max.
Core explained variable	ATL	330	0.458	1.395	0.004	8.960
Core explanatory variable	Dige	330	0.149	0.119	0.027	0.728
Control variable	AM	330	3487.998	2922.710	93.970	13,353.020
	AFP	330	11.638	3.523	4.040	20.384
	APS	330	0.655	0.152	0.355	0.971
	AIS	330	0.529	0.084	0.363	0.719
	UR	330	0.618	0.113	0.379	0.896
	ADR	330	0.125	0.109	0.004	0.696
Mechanism variable	Human	330	9.441	0.909	7.514	12.681
	TFP	330	1.467	0.289	1.000	2.530

5. Empirical Results and Discussion

5.1. Benchmark Regression Results

From a statistical perspective, results in Table 3 clearly show that the impact of the digital economy development level on the agricultural trade level is consistently positive and statistically significant at the 1% level. Without including control variables, the coefficient of Dige is 3.241; after incorporating control variables such as total agricultural machinery power and crop planting structure, the coefficient increases to 4.036. This indicates that, after controlling for potential confounding factors such as regional agricultural production conditions and policy support intensity, the promoting effect of the digital economy on agricultural trade becomes even stronger. This finding verifies the core proposition of

Hypothesis 1. On the one hand, emerging digital industries have broken the geographical barriers of traditional trade. On the other hand, technologies such as digital cold chains and intelligent customs clearance systems have shortened distribution links, reduced information asymmetry and logistics costs, and facilitate the bidirectional expansion of agricultural trade through both exports and imports [58–60].

Table 3. Baseline regression results.

Variables	(1)	(2)
	ATL	ATL
Dige	3.241 *** (0.523)	4.036 *** (0.643)
lnAm		−0.773 *** (0.242)
AFP		0.016 * (0.008)
APS		−8.825 *** (1.471)
AIS		5.047 *** (1.363)
UR		−5.347 *** (1.060)
ADR		0.074 (0.346)
_cons	−0.027 (0.084)	12.018 *** (2.270)
N	330	330

Notes: Standard errors in parentheses; * $p < 0.1$, *** $p < 0.01$.

5.2. Mechanism Analysis

5.2.1. Impact of the Digital Economy on Agricultural TFP

Column (1) of Table 4 represents the impact of the digital economy on agricultural TFP. The results indicate that digital economy development is positively associated with higher agricultural TFP, suggesting that digital technologies enhance production efficiency through mechanisms of technology penetration and factor reallocation. Digital tools such as intelligent irrigation systems and unmanned aerial vehicles facilitate precision agriculture by reducing input costs and increasing output efficiency per unit of land. In addition, big data analytics contributes to the optimization of cropping structures and the reduction in resource misallocation [61]. The enhancement of agricultural productivity directly strengthens the international competitiveness of agricultural products, expands the scale of trade, and allows greater benefits from the enlarged market scope, thereby promoting the overall level of agricultural trade [62]. Therefore, the conclusion supports Hypothesis 2.

Table 4. Regression results of mechanism analysis.

Variables	(1)	(2)
	TFP	**Human**
Dige	1.256 ***	1.027 ***
	(0.207)	(0.233)
InAm	−0.006	−0.071
	(0.078)	(0.088)
AFP	0.002	0.001
	(0.003)	(0.003)
APS	0.665	−0.840
	(0.474)	(0.534)
AIS	0.998 **	0.345
	(0.439)	(0.495)
UR	2.835 ***	4.880 ***
	(0.341)	(0.385)
ADR	−0.174	−0.018
	(0.111)	(0.126)
_cons	−1.383 *	7.171 ***
	(0.731)	(0.824)
N	330	330

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2.2. Impact of the Digital Economy on Rural Human Capital Level

Column (2) of Table 4 represents the impact of the digital economy on the level of rural human capital. The estimated coefficient is 1.027, confirming the empowerment mechanism of "skill training-learning effect-capacity transformation." The digital economy promotes various rural e-commerce training programs and livestreaming operation courses that enhance farmers' digital skills and market analysis capabilities, facilitating the transformation of trade participants from "traditional farmers" to "digital merchants." Meanwhile, the improvement of human capital accelerates the adoption and application of digital technologies, enabling farmers to more easily master operations such as cold chain logistics scheduling and cross-border payment processing, thereby forming a positive feedback cycle of "digital technology–human capital–trade growth." The continuous development of digital trade fosters technological innovation and human capital accumulation, driving the transformation of agricultural trade. At the same time, it helps reduce the cost of agricultural imports, improve trade conditions, and ultimately enhance the overall level of agricultural trade [48,50]. However, the core limitation of measuring the human capital related to the digital economy by average education is that "the educational level indicators cannot fully match the digital skill level", but the longer the education period, the stronger the adaptability and learning ability of digital tools and digital knowledge, which is conducive to improving their digital skills and literacy. Therefore, the findings confirm Hypothesis 3.

5.3. Heterogeneity Analysis

5.3.1. Regional Heterogeneity Analysis

This paper divides the research samples into eastern, central, and western regions. This division allows for an analysis of the regional heterogeneity in the impact of digital economy development on the level of China's agricultural trade (Table 5).

Table 5. Regression results of regional heterogeneity among eastern, central, and western China.

Variables	(1)	(2)	(3)
	Eastern	**Central**	**Western**
Dige	3.772 ***	−0.017	−0.030
	(1.245)	(0.058)	(0.040)
Control variables	Yes	Yes	Yes
_cons	30.238 ***	0.026	−0.115
	(5.052)	(0.078)	(0.085)
N	121	88	121

Notes: Standard errors in parentheses; *** $p < 0.01$.

Table 5 shows that the impact of digital economy development on the level of agricultural trade exhibits significant regional differentiation. In the eastern region, the coefficient of Dige is 3.772, which is significantly. In contrast, the coefficients for the central region (−0.017) and the western region (−0.030) are close to zero and statistically insignificant. This indicates that, at present, the digital economy effectively empowers agricultural trade only in the eastern region.

The observed regional disparity is likely driven by mismatches between digital infrastructure development and underlying industrial foundations [63–65]. The eastern region benefits from more advanced digital infrastructure, including higher broadband penetration and a greater concentration of cross-border e-commerce pilot zones, alongside a relatively mature agricultural industrial base. As a result, digital infrastructure enables more effective data collection, monitoring, and coordination across agricultural production, processing, and logistics, facilitating product standardization and reducing information asymmetries through digital platforms and intelligent customs systems.

Product standardization plays a key role in translating digital capabilities into market access by converting production data into grading, certification, and testing standards aligned with domestic and international requirements. This alignment allows digital technologies to integrate more efficiently with trade demand. In contrast, central and western regions face persistent constraints stemming from weaker digital infrastructure, homogeneous product structures, and limited availability of skilled personnel for digital trade operations, which restrict the conversion of digital economy development into concrete agricultural trade gains [54].

5.3.2. Heterogeneity in Agricultural Production Structure Between Northern and Southern Regions

Due to substantial differences in climate, geography, and other natural endowments between China's southern and northern regions, the structure of agricultural products produced in these two areas also varies considerably, leading to differences in trade adaptability. Therefore, this paper divides the research samples into northern and southern regions (Table 6).

Table 6 shows that the coefficient of the digital economy index (Dige) is significantly positive in both northern and southern regions, but the magnitude is substantially larger in the North (8.862) than in the South (2.583), indicating that northern regions benefit more from digital economy development in agricultural trade. This difference can be explained by variations in agricultural production characteristics and digital adaptability. The northern region primarily produces highly commercialized and standardized agricultural products, such as grain and livestock products (e.g., rice in Northeast China and beef and mutton in Inner Mongolia), which are more suitable for large-scale transactions through cross-border

e-commerce. For these products, digital supply chains can more effectively address issues related to quality control, traceability, and consumer trust.

Table 6. Regression results of regional heterogeneity between northern and southern China Variable.

Variables	(1)	(2)
	North	South
Dige	8.862 *** (1.035)	2.583 *** (0.930)
Control variables	Yes	Yes
_cons	9.438 *** (2.289)	15.694 *** (5.075)
N	165	165

Notes: Standard errors in parentheses; *** $p < 0.01$.

By contrast, agricultural production in the southern region is dominated by non-standardized and highly perishable products, including fruits, vegetables, and tea, which face greater challenges in quality grading and logistics. In 2023, the national low-temperature processing rate of agricultural products at the place of origin was only 32%, and for fruits and vegetables it was as low as 24%, indicating that many southern production areas lack adequate cold chain facilities. As a result, even when market access is achieved through digital platforms, post-harvest losses may occur due to cold chain disruptions. In comparison, the low-temperature processing rate of meat products reached 80% nationwide, suggesting that agricultural products in northern regions generally benefit from more developed cold chain logistics. The closer integration of cold storage infrastructure with digital supply chains allows digital technologies to be translated more directly into improved circulation efficiency.

5.3.3. Grain-Producing and Non-Grain-Producing Regions

Differences in national food security priorities and local development objectives have resulted in distinct agricultural orientations across regions in China. Grain-producing regions prioritize staple crop production for self-sufficiency, whereas non-grain-producing regions are more market- and trade-oriented, focusing on cash crops. Therefore, this paper divides the research samples into grain-producing regions and non-grain-producing regions to analyze the industrial development-oriented heterogeneity in the impact of digital economy development on China's agricultural trade level. The empirical results are presented in Table 7.

Table 7. Regression results of regional heterogeneity between northern and southern China.

Variables	(1)	(2)
	Grain-Producing Regions	Non-Grain-Producing Regions
Dige	0.189 *** (0.047)	3.528 *** (0.930)
Control variables	Yes	Yes
_cons	0.110 (0.138)	18.442 *** (3.595)
N	143	187

Notes: Standard errors in parentheses; *** $p < 0.01$.

The coefficient for grain-producing regions is 0.189, while that for non-grain-producing regions is 3.528. This difference likely reflects divergent production objectives. Grain-producing regions prioritize food security and production stability, where agricultural trade is more policy-driven and less responsive to market expansion. In contrast, non-grain-producing regions focus on highly commercialized cash crops, allowing digital technologies and platform-based business models to more effectively connect with international market demand and expand trade scale. Overall, these results support Hypothesis 4.

5.4. Endogeneity Test

The baseline regression outcomes may be subject to endogeneity concerns, particularly potential reverse causality. To mitigate this issue, the study applies an instrumental variable (IV) strategy. Specifically, we use the number of post offices in each province in 1984 as an instrument for digital economy development. This variable is selected as an instrumental variable for the following reasons. Historical postal infrastructure reflects early communication and information transmission capacity, which is closely related to the long-term evolution of modern digital infrastructure and the digital economy. Given the long time lag, the number of post offices in 1984 is plausibly exogenous to contemporary agricultural trade outcomes and is unlikely to affect current agricultural trade directly except through its influence on digital economy development.

The first-stage regression results, reported in Table 8, show that the historical postal infrastructure variable is strongly correlated with the current level of digital economy development. The corresponding first-stage F-statistic equals 14.450, indicating that the instrument is sufficiently strong. After correcting for endogeneity using this IV approach, the estimated coefficient remains positive and statistically significant, with a magnitude of 8.969. The results from the instrumental variable analysis further demonstrate the robustness of this study. Notably, the larger magnitude of the IV estimate relative to the OLS result may reflect a local average treatment effect, capturing the impact of digital economy development on regions whose digital infrastructure is more responsive to historical communication foundations.

Table 8. Results of endogeneity test.

Variables	**(1)**	**(2)**
	ATL	**Dige**
Dige	8.969 *** (1.575)	
L1_Dige		0.054 *** (0.009)
Control variables	Yes	Yes
_cons	−1.243 *** (0.414)	−0.093 (0.071)
F-statistic		14.450
Wald statistic	191.810	
N	300	300

Notes: Standard errors in parentheses; *** $p < 0.01$.

5.5. Robustness Test

The robustness checks summarized in Table 9 lead to several noteworthy conclusions. First, we reconstruct the digital economy indicator using an equal-weighting method across the 19 sub-indicators and re-estimate the model. The estimated coefficient of Dige remains positive and statistically significant at the 1% level, indicating that the main findings are not

driven by the specific weighting scheme employed in the entropy method. Second, when the dependent variable representing agricultural trade is substituted with the logarithm of total agricultural exports (lnout), the coefficient of Dige increases to 0.455, which is significant at the 10% level. Although the statistical significance declines slightly, the sign of the coefficient remains positive and aligned with the benchmark estimates. Taken together, these results indicate that the positive influence of digital economy development on China's agricultural trade persists across alternative specifications—whether the outcome variable reflects total agricultural trade or only agricultural exports. This consistency demonstrates that the main conclusions are robust and that the analysis does not suffer from issues related to variable definition bias.

Table 9. Robustness tests.

Variables	(1)	(2)
	Replace the Independent Variable	**Replacing the Dependent Variable**
Dige	4.575 *** (0.632)	0.455 * (0.275)
Control variables	Yes	Yes
_cons	6.721 *** (1.577)	3.610 *** (0.971)
N	330	330

Notes: Standard errors in parentheses; * $p < 0.1$, *** $p < 0.01$.

6. Conclusions and Policy Recommendations

6.1. Research Conclusions

Drawing upon both theoretical insights and empirical evidence, this study arrives at several key conclusions. First, the digital economy plays a clear and direct role in advancing China's agricultural trade. After controlling for agricultural production conditions, policy support, and other factors, this positive effect is further strengthened. Second, the influence of the digital economy on agricultural trade is not uniform across regions or industrial structures. From a spatial perspective, digital development demonstrates a notably stronger trade-enhancing impact in the eastern provinces compared with the central and western regions, and the effect is more substantial in northern China than in the southern areas. It should be noted that this stronger regional effect may be driven by imports, exports, or a combination of both. In particular, in eastern China, more developed digital infrastructure and cross-border e-commerce platforms may facilitate more efficient access to international agricultural markets, suggesting a potentially import-driven mechanism. From an industrial perspective, non-grain-producing regions benefit more from digital economy development than grain-producing regions. The core of this heterogeneity may lie in differences in digital infrastructure maturity, agricultural product characteristics, and production objectives, indicating that the impact of the digital economy on agricultural trade is not homogeneous and should be addressed through region-specific and targeted policies. Third, agricultural TFP and rural human capital serve as mediating mechanisms through which the digital economy indirectly promotes agricultural trade.

6.2. Policy Recommendations

First, accelerate the improvement of the national digital infrastructure network for agricultural trade. Priority should be given to addressing infrastructure bottlenecks in the central and western rural areas, particularly in 5G communication networks and digital cold chain logistics. Meanwhile, it is essential to promote digital trade models such as

cross-border e-commerce and intelligent customs clearance to reduce trade circulation costs and information asymmetry. Deep integration between agricultural machinery and digital technologies should also be encouraged to avoid the "diseconomies of scale" problem in traditional mechanization and to build a solid hardware foundation for the digital economy to empower agricultural trade.

Second, implement differentiated digital trade development strategies. The eastern region should leverage its advantages in digital economy infrastructure to develop high-end digital trade forms such as digital exhibitions and overseas warehouses, while promoting interregional cooperation to enhance the digital trade capacity of the central and western regions. The northern region should focus on standardized agricultural products such as grain and livestock, strengthening digital traceability and cold chain logistics systems to meet digital trade demands. The southern region, characterized by non-standardized products such as fruits, vegetables, and tea, should establish digital grading standards and full-chain traceability platforms to address challenges in standardization and quality certification. For grain-producing regions, under the premise of ensuring national food security, efforts should be made to moderately develop digital trade in high value-added processed agricultural products. In contrast, non-grain-producing regions should further expand new digital trade formats such as cross-border live-streaming e-commerce, accurately matching international market demand. To enhance the effectiveness of the mediating mechanisms, efforts should be made in two key areas. Continue to expand the digital economy's transformation of agricultural production by promoting technologies such as smart irrigation, UAV crop protection, and big data-based optimization of planting structures in major agricultural regions.

6.3. Research Limitations

This study has two main limitations. First, the analysis relies on provincial- and national-level macro data, which help reveal overall patterns but cannot capture the behavioral differences in micro entities such as farmers, firms, or e-commerce platforms. Future studies may use micro survey data or firm- and platform-level data to better identify individual decision-making mechanisms. Second, the empirical model does not account for potential spatial spillover effects of the digital economy. In reality, digital infrastructure, platforms, and logistics networks exhibit strong spatial linkage, and one region's digital development may influence neighboring regions. Future research could apply spatial econometric models to more fully examine these spatial interaction effects.

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