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Mechanism and Policy Pathways of the Digital Economy Empowering New Productivity in Agriculture

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Abstract
The digital economy has become a key driver of agricultural transformation and upgrading, as well as the cultivation of new agricultural productive forces. However, the mechanisms of action and regional differences of this process remain insufficiently understood. Drawing on the theories of technology acceptance and diffusion and resource allocation, and using panel data from 283 prefecture-level cities between 2011 and 2022, an index of new agricultural productive capacity was constructed. The impact of the digital economy on new agricultural productive capacity, the underlying mechanisms, and the effects of relevant policies were analyzed systematically. Results show that the digital economy significantly promotes the development of new agricultural productive capacity, and this conclusion remains robust across multiple tests. Further analysis indicates that the enabling role of the digital economy is more pronounced in grain-producing regions, regions with balanced production and sales, areas with high digital technology penetration, and national big data comprehensive pilot zones, while its impact is weaker in major consumption regions and areas with lower technological levels. Moreover, industrial upgrading effects, factor allocation effects, and innovation-driven effects act as key pathways through which the digital economy enhances new agricultural productivity. Government-effective investment and rural human capital are found to exert significant positive moderating effects on this enabling role. In addition, the national e-commerce demonstration city pilot policy and rural e-commerce significantly strengthen the development of new agricultural productivity. This study reveals the mechanisms and context-dependent characteristics of how the digital economy enables agricultural development, enriches the theoretical research on agricultural digital transformation, and provides empirical evidence and policy insights for advancing agricultural digitalization and rural revitalization tailored to local conditions.

Keywords
digital economy; new agricultural productivity; rural e-commerce

Introduction

In recent years, the global digital economy has experienced rapid growth, becoming a key driver of economic growth and industrial transformation. According to data from the China Academy of Information and Communications Technology's "Global Digital Economy White Paper (2024)," the combined digital economy of the United States, China, Germany, Japan, and South Korea exceeded 33 trillion US dollars in 2023. Among these, the Asia-Pacific region saw the fastest growth, with the enabling effects of the digital economy on agriculture, manufacturing, and services becoming increasingly evident. China's digital economy has consistently ranked second globally in terms of total size, surpassing 50 trillion yuan in 2023, accounting for 42.8% of GDP, and has also made remarkable progress in the digital transformation of agriculture. International experience shows that deep integration of digital technology with agriculture can effectively drive the transformation of agricultural production methods from traditional, resource-dependent inputs to data- and technology-driven approaches. For example, the Netherlands has leveraged IoT and precision farming technologies to become a global leader in agricultural product exports, while Israel has achieved efficient agricultural production under resource-scarce conditions through agricultural informatization and drip irrigation technologies (Imtiaz et al., 2025). However, given differences in digital infrastructure levels, industrial structures, and policy support across countries and regions, the role of the digital economy in enhancing agricultural productivity varies. This variation makes exploring the mechanisms and implementation pathways of the digital economy in fostering new-quality agricultural productivity in China theoretically relevant and practically meaningful (Hervas-Oliver et al., 2021).

Existing research explains the phenomenon of the rapid development of the global and Chinese digital economies and their considerable impact on agricultural transformation from three perspectives: First, the theory of technological innovation diffusion posits that once new-generation information technologies (such as the Internet of Things, artificial intelligence, and big data) surpass a "critical adoption rate," they will rapidly spread across various industries (Ho, 2022). Countries such as the United States and the Netherlands have taken the lead in agricultural digitization due to their well-developed digital infrastructure and mature technology applications, enabling efficient translation of research outcomes into agricultural applications (Andrey et al., 2025). China's digital economy has grown to become the second largest in the world in recent years because of the rapid popularization of technologies such as mobile internet and digital finance, which have considerably lowered the technological barriers to agricultural production models and created conditions for the formation of new agricultural productive forces (Jiang & Murmann, 2022). Second, the theory of industrial integration emphasizes that technological penetration and factor reallocation across industries can give rise to new forms of productive forces (Zou, 2024). By deeply integrating data and algorithms with agricultural production, the digital economy not only optimizes traditional processes such as planting and breeding but also extends to the entire industrial chain, including processing, logistics, and sales, driving the transformation of agriculture from resource-driven to data-driven and technology-driven (Ouyang, 2024). The extent of this cross-border integration determines the scope in which the digital economy can empower new agricultural productivity. Third, institutional economics theory suggests that policy support and institutional arrangements are crucial for the successful implementation of new technologies in agriculture (Bachev, 2024). China has introduced a series of policies in areas such as digital infrastructure development, rural e-commerce support, and digital inclusive finance, thereby reducing the institutional costs for agricultural entities to adopt digital technologies (Li & Zhang, 2024). Especially under the institutional frameworks of China's National E-commerce Demonstration Cities and the Rural Revitalization Strategy, the empowerment of agriculture by the digital economy is no longer a scattered and spontaneous process but has been incorporated into top-level design and long-term development plans, thereby laying the institutional foundation for the cultivation of new-quality agricultural productivity (Cai & Wang, 2025). Unfortunately, while existing research on the digital economy's empowerment of new-quality agricultural productivity has achieved certain results in theoretical logic and pathway exploration, it still has shortcomings. First, it is overly macro-oriented and lacks a micro-level analysis of the pathways and mechanisms through which the digital economy influences new-quality agricultural productivity. Most existing studies remain at the national or provincial level, emphasizing the correlation between the overall development level of the digital economy and agricultural transformation, but rarely revealing its role in the "digital technology–factor flow–production process–output enhancement" chain (Du et al., 2022). Second, the measurement dimensions are too narrow. The indicator systems for new-quality agricultural productivity are mostly based on macro-level statistics or theoretical abstractions, ignoring the constraints imposed by differences in factor structures, technology application levels, and supply chain completeness at the prefectural city level on the enabling effects of the digital economy. Thus, explaining the underlying reasons for the varying outcomes across regions becomes difficult under the same level of digital economy development (Wang et al., 2024). Third, the exploration of intermediary and regulatory mechanisms is insufficient. While existing research has highlighted the roles of industrial upgrading, factor allocation, and innovation-driven development, it lacks systematic empirical testing and overlooks how conditional variables, such as government investment and rural human capital, can amplify or weaken the enabling effects of the digital economy on agriculture (Wang et al., 2022). These shortcomings prevent existing theories from fully explaining the empirical phenomenon of "homogeneous digital inputs and heterogeneous agricultural outcomes."

To address the above shortcomings, this study proposes interpreting the findings using technology acceptance and diffusion theory (TADT) and resource orchestration theory (ROT). According to TADT, the adoption of new technologies is not only determined by their technical performance but is also constrained by users' perceived ease of use, perceived usefulness, and social network influences (Bashir et al., 2022). In the agricultural sector, even with digital economic infrastructure in place, the speed and depth of technology adoption among farmers and agricultural operators may still vary considerably due to differences in cognition, skill levels, and risk preferences. This variation can lead to the phenomenon of "homogeneous inputs but heterogeneous outputs" across different regions and entities despite identical digital investments. By contrast, ROT emphasizes that when facing new environments and technologies, enterprises or organizations must undergo three processes—resource acquisition, integration, and utilization—to achieve dynamic resource matching and value creation (Kaur, 2023). In the process of digital economy empowerment of agriculture, agricultural operators and local governments must effectively orchestrate digital technology, capital, human resources, and data to unlock their potential to drive new agricultural productivity. This implies that the digital economy does not directly translate into productivity but must pass through two critical "filters"—technology adoption (willingness and ability to adopt) and resource orchestration (integration and utilization efficiency of elements)—to take root in agricultural contexts. Therefore, this study introduces a theoretical "technology acceptance–resource integration" dual-path mechanism framework to explain the differentiated performance of the digital economy in empowering new-quality agricultural productivity across different regions, agricultural functional zones, and levels of digital technology. It further identifies how government investment and rural human capital can amplify or weaken this process. Thus, this study aims to address the following research questions: (1) How does the digital economy influence new-quality agricultural productivity through the technology adoption and resource allocation pathways? (2) How does this mechanism manifest differently under varying regional and factor endowment conditions? (3) How do government investment and human capital regulate the efficiency of the technology adoption–resource allocation pathway? This study not only enriches the theoretical framework for cultivating new-quality agricultural productivity but also provides more actionable policy recommendations to empower agriculture precisely through the digital economy.

The innovative points and marginal contributions of this study are as follows: (1) For the first time, an index of new-quality agricultural productivity has been constructed at the prefecture-level city level, expanding the spatial and methodological boundaries of measuring new-quality productivity. Existing studies have largely remained at the provincial or macro level, making it difficult to capture internal regional differences. This study adopts a three-dimensional approach focusing on agricultural new-quality laborers, agricultural new-quality labor resources, and agricultural new-quality labor objects. Using the entropy weight method, it establishes a comprehensive measurement system encompassing multiple indicators, such as production efficiency, technological level, and green development degree, providing high-resolution data to support precise analysis of the enabling effects of the digital economy. (2) It constructs a "technology adoption–resource allocation" dual-path mechanism framework, systematically revealing the micro-level logical chain through which the digital economy influences agricultural new-quality productivity. Breaking away from the traditional research paradigm that directly links the digital economy to productivity levels, this study examines the enabling effects of the digital economy on agriculture through three intermediary pathways: industrial upgrading, factor allocation, and innovation-driven effects. It also introduces the moderating roles of government effectiveness and rural human capital, thereby enriching research on the mechanisms through which the digital economy enables agriculture. (3) Using panel data from 283 prefecture-level cities from 2011 to 2022, combined with various robustness tests and heterogeneity group analysis, this study precisely identifies the differentiated enabling effects of the digital economy in different agricultural functional zones and at different levels of digital technology, providing empirical evidence for regional classification and policy-making. (4) Incorporating rural e-commerce and national e-commerce demonstration city pilot policies into the analytical framework, this study fills the existing research gap on the impact of e-commerce on agricultural productivity, revealing the practical value of e-commerce development in optimizing industrial chains, promoting factor mobility, and enhancing production efficiency. (5) Combining practical challenges with targeted policy recommendations, this study addresses the practical dilemma of "homogeneous digital inputs and heterogeneous agricultural outcomes," providing operational pathways for the digital economy to drive high-quality agricultural development and rural revitalization.

Theoretical Analysis and Research Hypotheses

Direct Impact of the Digital Economy on New Agricultural Productivity

From the perspectives of TADT and resource mobilization theory, the digital economy plays a dual role in promoting the development of new agricultural productivity. First, TADT emphasizes that the widespread adoption of new technologies depends not only on their technical performance but also on users' perceived usefulness, perceived ease of use, and the diffusion effects of social networks (Lu et al., 2023; Al-Emran, 2023).

In an agricultural context, if the tools provided by the digital economy, such as big data, the Internet of Things, cloud computing, and artificial intelligence, are perceived by farmers and agricultural operators as "useful and easy to use" and spread rapidly within rural social networks, they can remarkably enhance the intelligence and precision of agricultural production. For example, through digital agricultural machinery and real-time monitoring systems, farmers can more accurately manage water and fertilizer inputs and predict pest and disease outbreaks, thereby reducing costs and improving yields and quality. Once the adoption rate of these technologies crosses the "critical adoption threshold," a rapid diffusion effect emerges, driving the entire agricultural production system to transition from experience-driven to data-driven, thereby enhancing agricultural productivity (Ogunyiola & Gardezi, 2022). Second, ROT posits that technology itself does not automatically translate into productivity; it also requires agricultural entities and local governments to coordinate effectively the three stages of resource acquisition (acquiring)–integration (bundling)–utilization (leveraging) (Khayyam et al., 2025). The enabling process of the digital economy essentially involves dynamically integrating and efficiently utilizing elements such as data, capital, human resources, and technology through platform-based and intelligent means. For example, local governments can use digital platforms to integrate resources from agricultural research institutions, agricultural input suppliers, and logistics companies to form a digital agricultural ecosystem spanning the entire production, processing, and sales chain. Agricultural enterprises can use digital financial tools to obtain low-cost capital, integrate and upgrade agricultural machinery and technology, and achieve large-scale and standardized production. Through effective resource orchestration, the digital economy not only optimizes the allocation of agricultural factors but also extends the industrial chain and upgrades the value chain, thereby providing continuous momentum for new agricultural productivity. In summary, the technology adoption and diffusion pathway ensures that digital technologies are widely adopted and rapidly penetrate all aspects of agricultural production, while the resource allocation pathway ensures that these technologies are effectively combined with capital, human resources, data, and other factors to unleash synergistic effects. The two pathways interact to jointly drive the transformation of agriculture from a traditional, factor-driven model to a data- and technology-driven model, achieving comprehensive improvements in production efficiency, green development levels, and technological content. Therefore, this study proposes the following hypothesis:

H1: The digital economy effectively promotes the development of new agricultural productivity.

Impact Mechanism of Digital Economy Empowering the Cultivation of New Productivity in Agriculture

From the perspective of TADT, the diffusion of core technologies in the digital economy (such as the Internet of Things, cloud computing, big data, and artificial intelligence) in the agricultural sector depends not only on the inherent performance advantages of these technologies but also on the extent to which agricultural stakeholders perceive their usefulness and ease of use and the speed at which they spread within agricultural social networks. When these digital technologies are widely adopted and deeply integrated into agricultural production, processing, and distribution, they trigger systemic transformations, leading to industrial upgrading, factor allocation, and innovation-driven effects. First, the industrial upgrading effect stems from the cross-industry penetration capability of digital technologies after surpassing the "critical adoption rate." Digital economy platforms enable agriculture to integrate deeply with industries such as processing, logistics, and tourism, thereby extending the agricultural industrial chain and upgrading the value chain (Ye & Jiang, 2025). For example, precision farming and big-data-based market forecasting not only improve the quality and added value of agricultural products but also promote the transition from single-product production to diversified, integrated development (Tian et al., 2022). This transformation is essentially an upgrade of the agricultural industrial structure, consistent with the path-dependent logic of optimizing resource allocation. Second, the factor allocation effect can be explained using ROT. This theory posits that productivity improvements depend not only on the quantity of resources but also on the dynamic optimization of resources in the acquisition, integration, and utilization phases. The digital economy, through information platforms and intelligent management systems, remarkably enhances the liquidity and matching efficiency of production factors such as land, labor, capital, and technology, reducing resource misallocation across regions and industries (Wang, 2024). For example, IoT technology enables real-time monitoring of soil and meteorological data, allowing precise matching of water and fertilizer inputs with crop needs, thereby reducing resource waste and increasing agricultural productivity (Xing & Wang, 2024). Finally, the innovation-driven effect is manifested in the digital economy's promotion of agricultural technological innovation and management model innovation by reducing information asymmetry, expanding financing channels, and stimulating the vitality of innovation entities. Agricultural entities in a digital market environment can obtain real-time market feedback through data analysis and platform transactions, enabling them to adjust product structures and technical solutions quickly (Deichmann et al., 2016). Additionally, the integrated application of big data and artificial intelligence provides efficient support for innovation in new variety breeding, pest and disease prediction, and the optimization of control strategies, accelerating the commercialization of research outcomes (Rai, 2022). In summary, the digital economy not only promotes the widespread application of new agricultural productivity through technology adoption and diffusion pathways but also optimizes the integration and utilization efficiency of agricultural production factors through resource orchestration pathways. This process simultaneously drives industrial upgrading, factor allocation, and innovation, synergistically promoting the transformation of agriculture from a traditional resource-driven model to a data- and technology-driven one. Therefore, this study proposes the following hypothesis:

H2: The digital economy empowers the development of new agricultural productivity through industrial upgrading, factor allocation, and innovation-driven effects.

Within the framework of TADT, the process by which the digital economy empowers new productive forces in agriculture is not merely a matter of technology supply but also requires agricultural entities to perceive usefulness and ease of use, and to achieve diffusion efficiency within rural social networks. When rural human capital levels are high, farmers and agricultural operators are more likely to master digital tools, understand their specific value in production, sales, and management, and disseminate them more quickly within familiar networks and supply chains, thereby enhancing the efficiency of digital economy empowerment (Ma et al., 2023). Conversely, in regions with lower human capital, even if the technological infrastructure is in place, the speed of technology adoption and depth of application remain limited, leading to “homogeneous digital inputs and heterogeneous agricultural outcomes” (Neumeyer et al., 2020). Therefore, the improvement of human capital provides the “cognitive soil” and “skill carriers” for the diffusion and deep application of digital technology, amplifying the effect of the digital economy in transforming into new agricultural productivity. Within the framework of ROT, the digital economy must undergo three stages to function effectively: resource acquisition (acquiring) - integration (bundling) - and utilization (leveraging). Government investment, as an external resource supply mechanism, can address rural infrastructure shortcomings during the acquisition phase; facilitate the cross-sectoral flow of information, technology, and capital during the integration phase; and reduce application costs for agricultural entities through demonstration projects and fiscal subsidies during the utilization phase, thereby shortening the cycle from technology introduction to productivity transformation (Hidayat et al., 2024). Especially under the impetus of the digital economy, government investment can enhance the efficiency of factor matching and the level of industrial chain coordination by improving “hardware conditions” such as broadband networks, agricultural IoT nodes, and smart agricultural machinery, as well as by constructing agricultural data platforms and promoting digital finance (Meng & Zhao, 2022). Such investments not only directly enhance agricultural digitalization capabilities but also, indirectly, expand the breadth and depth of technology adoption, thereby significantly strengthening the positive role of the digital economy in fostering new productive forces in agriculture. In summary, rural human capital and effective government investment play distinct roles in the two pathways of technology adoption and resource allocation, respectively: “increasing technology adoption rates” and “optimizing the integration and utilization of factors.” Both have an amplifying effect on the digital economy’s empowerment of new-quality agricultural productivity. When human capital and government investment levels are insufficient, the enabling role of the digital economy is “weakened” or “masked;” conversely, when both levels are high, this role is considerably amplified. Therefore, the following hypothesis is proposed:

H3: Enhancing human capital in rural areas and increasing effective government investment strengthen the impact of the digital economy on enhancing new agricultural productivity.

Research Design

Sample Selection and Data Sources

This study used data from 283 Chinese cities between 2011 and 2022 as its sample. Given that China established national e-commerce demonstration cities in 2011 and the digital economy began to take shape, this study set its starting point at 2011. Rural data for prefecture-level cities was relatively complete in 2022. Given the availability of rural data at this administrative level, this study sets 2022 as the cutoff year for its analysis. The original data used in this study were sourced from the “China Rural Statistical Yearbook,” “China Urban Statistical Yearbook,” and provincial statistical yearbooks. Missing data were imputed using linear interpolation. By comparing trends in the data before and after interpolation, the reasonableness of the interpolation results was ensured, and the data were subjected to trimmed-mean processing.

Variable Definitions

Dependent Variables

Agricultural New Quality Productivity (ANQP). The focus of this study is on how to construct new quality productivity. The study starts from the “new” characteristics, constructing an indicator system for agricultural new-quality productive forces at three levels: agricultural new-quality laborers, agricultural new-quality labor tools, and agricultural new-quality labor objects. The specific indicators are shown in the table below. The weights of each indicator were calculated using the entropy weight method, and the final indicators for agricultural new-quality productive forces in each prefecture-level city from 2011 to 2022 were obtained (Qin et al., 2025).

(1) New-type agricultural workers. From the perspective of workers, highly skilled agricultural talent is the primary factor in new-type agricultural productivity. Agricultural science personnel with relevant professional skills, innovative thinking, and high labor quality contribute to advancing new-type agricultural productivity and high-quality agricultural development (Christiaensen et al., 2021). This study examined new-quality agricultural

workers from three aspects: labor productivity, worker quality, and worker spirit (Huang et al., 2024). Specifically, labor productivity is composed of three elements: economic income, agricultural output, and labor efficiency, represented by per capita income of farmers, comprehensive grain production capacity, and agricultural labor productivity, respectively. Worker quality is measured by two aspects: the average years of education per capita in rural areas and the proportion of education expenditure. The worker spirit is indirectly measured through the Engel coefficient of farmers.

(2) New-type agricultural labor resources. The “newness” of agricultural labor resources primarily manifests in the improved efficiency of agricultural production tools and their technological, intelligent, and digital transformation (Abiri et al., 2023). Building on existing research, this study evaluated new types of agricultural labor resources from two perspectives: material labor resources and intangible labor resources (Ren et al., 2024). Material labor tools were reflected in the basic conditions of rural production and resource output levels. The basic conditions of rural production are measured by two aspects: per capita total power of agricultural machinery and the application of pesticides and fertilizers. Resource output levels are reflected by indicators such as agricultural output rate and land output rate. Intangible labor tools are measured by the level of technological development, specifically represented by the number of agricultural patents.

(3) New-type labor objects in agriculture. Based on the characteristics of new-type productive forces, technological and green elements are the core of new-type labor objects in agriculture, representing an effective combination of green agriculture and smart agriculture (Yin et al., 2022). Therefore, this study developed new types of labor objects in agriculture, based on nonphysical labor objects and green physical labor objects. Nonphysical labor objects are primarily measured from the perspective of information technology levels, specifically represented by the total volume of rural telecommunications services and the digitalization level of rural areas. Green physical labor objects are evaluated from three aspects: green transformation, environmental construction, and green ecology. This includes comprehensive utilization rates of livestock and poultry manure, sanitation toilet coverage rates, rural greening rates, and the proportion of administrative villages that process household waste, among other factors, to comprehensively assess the greenification level of labor objects.

Core Explanatory Variables

Digital Economy (Digit). This study examined the development of the internet and digital finance, using the following indicators to measure the level of internet development: the number of internet users per 100 people, the proportion of employees in computer services and software, the total volume of telecommunications services per capita, and the number of mobile phone users per 100 people. The Digital Inclusive Finance Index was used to measure the level of digital finance development (Al-Smadi, 2023). The specific indicators are as follows:

Table 1. Indicator System for New Agricultural Productivity

New agricultural productivity	New Quality in Agriculture Workers	Labor productivity	Economic income	Per capita net income of farmers (yuan)	+
			Agricultural output	Total grain production capacity (10,000 tons)	+
			Labor productivity	Agricultural labor productivity (yuan/person)	+
		Worker quality	Average years of schooling per capita in rural areas	Average years of education among rural residents (years)	+
			Share of education expenditure	Percentage of rural residents' expenditure on education and culture (%)	+
		Worker spirit	Engel coefficient	Engel coefficient (%) for rural residents	−
	New Quality in Agriculture Means of Labor	Material means of production	Basic conditions	Total agricultural machinery power per capita (kilowatts)	+
				Pesticide and fertilizer application volume (10,000 tons)	−
			Resource output level	Agricultural productivity	+
				Land productivity	+
		Intangible labor resources	Level of scientific and technological innovation	Number of agricultural patents	+
	New Quality of Agriculture Object of Labor	Nonphysical labor objects	Level of informatization	Total rural telecommunications business volume (population ratio * total telecommunications business volume)	+
				Level of digitalization in rural areas	+
		Green physical labor objects	Green conversion	Comprehensive utilization rate of livestock and poultry manure (%)	+
			Environmental development	Sanitation coverage rate (%)	+
				Percentage of administrative villages that process household waste (%)	+
			Green ecology	Rural greening rate (%)	+

The formula for replacing the total volume of rural telecommunications services is as follows:

$$Total\ rural\ telecommunications\ business\ volume = \frac{per\ capita\ disposable\ income\ of\ rural\ residents}{per\ capita\ disposable\ income} \times Total\ telecommunications\ business\ volume \quad (1)$$

Table. 2. Digital Economy Indicator System

Digital economy	Level of Internet development	Number of Internet users per 100 people
		Percentage of computer service and software professionals
		Total telecommunications services per capita
		Number of mobile phone users per 100 people
	Level of digital finance development	Digital Financial Inclusion Index

Control Variables

To enhance the explanatory power and robustness of the regression model, this study incorporated multiple macroeconomic and socio-developmental control variables in the empirical analysis to mitigate the interference effects of regional development disparities on the relationship between the digital economy and agricultural new-quality productivity: The first variable is the degree of openness (Open), as regional openness levels directly influence the speed and scale of cross-border inflows of capital, technology, and information (Tang et al., 2022). Regions with higher openness are more likely to adopt advanced digital technologies, agricultural equipment, and management concepts, thereby exerting an external driving effect on agricultural new-quality productivity. If not controlled for, the positive effects of the digital economy may be misinterpreted as stemming from the spillover effects of foreign investment and external technologies. Therefore, controlling Open can isolate the independent impact of foreign trade and foreign investment on the new quality of agricultural productivity, avoiding confusion between external openness advantages and local digital economic development effects. The second is the degree of government intervention (GOV), measured by the proportion of government fiscal expenditure to GDP, which reflects the degree of public-sector dominance over economic activities (Ahuja & Pandit, 2020). In the agricultural sector, higher government intervention may directly enhance agricultural infrastructure and production capacity through subsidies, project investments, and policy guidance. However, excessive intervention may also distort resource allocation and suppress the market-driven flow of factors. Controlling for GOV isolates the independent impact of fiscal policy strength on agricultural productivity, ensuring that identified digital economy effects are not distorted by differences in policy intensity. The third variable is urbanization level (Urban), which reflects changes in population spatial distribution and urban–rural structure (Zhang et al., 2022). Urbanization may indirectly enhance the application level of the rural digital economy by improving infrastructure and promoting factor mobility; by contrast, it may also weaken agricultural production capacity due to the outflow of agricultural labor. Controlling the Urban variable can prevent the dual effects of urban–rural structural changes on agricultural productivity from being mistakenly attributed to the development of the digital economy itself. The fourth is market size (Market), which is the ratio of total social retail sales to GDP, reflecting regional market demand potential and consumption vitality (Wang et al., 2022). Regions with large demand scales and high consumption levels are more likely to stimulate digital upgrades and quality improvements on the agricultural supply side. If the Market is not controlled, the digital economy's driving role in new-quality agricultural productivity in large markets may be overestimated. Therefore, controlling for market size can isolate the direct impact of market demand strength on agricultural production upgrades. The fifth variable is internet penetration rate (Inter), measured as the ratio of broadband internet users to the population and serving as a direct indicator of the prevalence of digital infrastructure (Na et al., 2020). Regions with high internet penetration rates enable agricultural operators to more easily access information, utilize e-commerce, and connect to digital service platforms, thereby naturally achieving higher levels of new-type productive capacity. If this variable is not controlled for, the effects of the digital economy may be overstated, as some of the achievements stem from the inherent advantages of infrastructure rather than subsequent investments in the digital economy. In summary, the aforementioned control variables effectively isolate the direct influence of regional development foundations, policy environments, population structures, market demand, and digital infrastructure on agricultural new-quality productive capacity, thereby ensuring that the coefficients identified in the regression results more accurately reflect the enabling effects of the digital economy itself. The variables and calculation methods used in this study are detailed in Table 3.

Table 3. Explanation of Relevant Variables

Variable type	Variable name	variable symbol	Calculation method
Explained variable	New agricultural productivity	*ANQP*	Entropy weighting method
Explanatory variable	Rural digital economy	*Digit*	Entropy weighting method
Control variables	Degree of openness	*Open*	Total imports and exports/regional gross domestic product
	Level of urbanization	*Urban*	Urban population/total population
	degree of government intervention	*Gov*	General government expenditure/regional gross domestic product
	Market size	*Market*	Total retail sales of consumer goods/Gross domestic product
	Internet penetration rate	*Inter*	Number of Internet broadband access users/permanent resident population

Descriptive Analysis

As shown in Table 4, the maximum value of the agricultural new-quality productivity index is 0.573, the minimum value is 0.0342, and the standard deviation is 0.0734. This result indicates that the overall level of agricultural new-quality productivity is relatively low, with agricultural production efficiency and technology still at low levels. The intrinsic value and potential of agricultural new-quality productivity have not yet been fully realized, leaving considerable room for further development. The maximum value for the digital economy development level is 0.848, the minimum value is 0.0321, and the mean is 0.341. This result indicates that the digital economy has already developed to some extent, but considerable disparities between different prefecture-level cities remain because of differences in digital infrastructure and the focus of supporting industries across prefecture-level cities.

Table 4. Descriptive statistics

VARIABLES	(1)	(2)	(3)	(4)	(5)
	N	Mean	Sd	Min	Max
ANQP	3,396	0.224	0.0734	0.0342	0.573
Open	3,396	0.177	0.282	-0.0201	2.491
Urban	3,396	0.565	0.162	-0.703	1.178
Gov	3,396	4.975	2.408	-0.0980	23.12
Inter	3,396	25.60	14.98	0	125.9
Market	3,396	15.66	1.065	5.472	19.14
Digit	3,396	0.341	0.116	0.0321	0.848

Results Analysis

Benchmark Regression

This study constructed a two-way fixed benchmark regression model to examine the impact of digital economic development on the new quality of agricultural productivity. In this model, $ANQP_{it}$ is the dependent variable, representing the level of development of the new quality of agricultural productivity in city i in year t; $Digit_{it}$ is the explanatory variable, representing the level of development of the digital economy in city i in year t; and the estimated value of the coefficient $\gamma_1\gamma_1$ reflects the direction and extent of the impact of the digital economy on the new quality of agricultural productivity. Additionally, X is the control variable group, λ_i and δ_t respectively reflect the individual and year fixed effects, and μ_{it} is the random disturbance term.

$$ANQP_{it} = \beta_1 + \gamma_1 Digit_{it} + \varphi_1 X_{it} + \lambda_i + \delta_t + \mu_{it} \tag{2}$$

Columns (1)–(2) present the benchmark regression results for the impact of the digital economy on agricultural productivity. Column (1) shows the results of a two-way fixed-effects regression without control variables, while Column (2) presents the results of a two-way fixed-effects regression with control variables included. The regression results indicate that the digital economy has a considerable promotional effect on agricultural productivity. After incorporating control variables, the coefficient estimate for rural digital economy and rural e-commerce is 0.106, which is statistically significant at the 1% confidence level. This result implies that for every 1% increase in the digital economy, the development level of agricultural new-type productive capacity increases by an average of 0.106%. This implication suggests that in cities with more developed digital economies, agricultural new-type productive capacity can achieve greater development.

Table 5. Benchmark Regression Analysis

VARIABLES	(1)	(2)
	ANQP	*ANQP*
Digit	0.112***	0.106***
	(8.84)	(8.42)
Open		-0.027***
		(-6.93)
Urban		0.019***
		(2.65)
Gov		-0.001***
		(-4.28)
Inter		0.000
		(0.33)
Market		-0.003**
		(-2.37)
Individual fixed effects	YES	YES
Time fixed effect	YES	YES
Constant	0.149***	0.197***
	(38.72)	(9.53)
Observations	3,396	3,396
R-squared	0.627	0.636
Number of t	283	283
F test	0	0
r2_a	0.592	0.601
F	434.4	318.5

Robust t-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Robustness Analysis

To verify the robustness of the above results, this study conducted tests using three methods: endogeneity tests, sample reduction, and exclusion of policy interference.

Endogeneity Test

As discussed earlier, the development of the digital economy has a considerable promotional effect on the new quality of agricultural productivity. However, the improvement in agricultural productivity quality also drives the further development of the digital economy. This study fully considered the sustained nature of the digital economy, and the development of the new quality of agricultural productivity may be influenced by the prior development of the digital economy. To address potential endogeneity issues, this study introduced the digital economy from the previous period as an instrumental variable for a 2SLS regression. As shown in the table below, the first-stage regression coefficients are considerably greater than 0, indicating a significant correlation between the instrumental variable and the endogenous variable. The results pass the unidentifiability and weak instrumental variable tests. In the second stage, the results remain significant after using the instrumental variable, effectively demonstrating that the digital economy contributes to the development of new-quality agricultural productivity.

Table 6. Robustness Test (1): Instrumental Variable Test

VARIABLES	(1)	(2)
	First	Second
	Digit1	*ANQP*
L.Digit	0.999***	
	(191.39)	
Digit		0.578***
		(119.21)
Control variables	control	control
Individual fixed effects	YES	YES
Time fixed effect	YES	YES
Constant	-0.007	-0.050***
	(-0.78)	(-6.37)
Observations	3,113	3,113
R-squared	0.936	0.860

t-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Sample Reduction

Given the reduced supply of rural labor during the pandemic, seasonal planting was severely impacted, production materials were in short supply, and the market faced issues such as declining demand and supply chain disruptions, resulting in a decline in rural productivity. To eliminate the impact of the pandemic on economic development in 2020 and 2021, this study excluded 2020 and 2021 data and reran the regression. The regression results are shown in Table 7, Columns (1) - (2). Column (1) presents the regression results without control variables, while Column (2) presents the regression results with control variables. By examining the results, we can confirm that the aforementioned conclusion remains valid, namely, the development of the digital economy contributes to the advancement of new-quality agricultural productivity. Second, some cities have higher levels of economic development and receive greater national policy support. To mitigate the selection bias in the sample, the regression was conducted again after excluding the four super-tier-one cities of Beijing, Shanghai, Guangzhou, and Shenzhen (Chao et al., 2024). The regression results are shown in Column (3) of Table 7, and the results remain valid. Additionally, to comprehensively consider sample selection and mitigate potential estimation biases, this study further excluded data from 2020 and 2021, as well as data from the four megacities of Beijing, Shanghai, Guangzhou, and Shenzhen, and reran the regression. The regression results are shown in Column (4) of Table 7, and the results remain valid.

Table 7. Robustness Test (2): Sample Deletion

VARIABLES	(1)	(2)	(3)	(4)
	ANQP	*ANQP*	*ANQP*	*ANQP*
Digit	0.107***	0.101***	0.094***	0.091***
	(7.78)	(7.41)	(7.58)	(6.79)
Constant	0.150***	0.189***	0.192***	0.181***
	(36.49)	(8.05)	(9.47)	(7.90)
Control variables	None	control	control	control
Individual fixed effects	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Observations	2,830	2,830	3,348	2,790
R-squared	0.633	0.644	279	0.643
Number of t	283	283	0.635	279
F test	0	0	0	0
r2_a	0.591	0.602	0.600	0.602
F	438.3	304.7	312.5	300.3

Robust t-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Eliminating Policy Interference

The Smart City Policy and the Broadband China Policy effectively reflect China's emphasis on the digital economy. The implementation of these policies may influence the extent to which different cities' digital economies affect the development of new agricultural productivity. Therefore, this study introduced the two dummy variables "Smart City" and "Broadband China" for further regression analysis. The regression results are shown in Table 8. Columns (1) and (2) present the regression results controlling for "Smart City" and "Broadband China," respectively, indicating that the aforementioned findings remain valid, i.e., the development of the digital economy contributes to the advancement of new-quality agricultural productivity. Additionally, this study conducted another regression with both dummy variables, as shown in Column (3) of Table 8, and the regression results confirm that the aforementioned findings remain valid.

Table. 8. Robustness Test (3): Excluding Policy Interference

VARIABLES	Smart city	Broadband China	Simultaneous control
	(1)	(2)	(3)
	ANQP	*ANQP*	*ANQP*
Digit	0.106***	0.107***	0.106***
	(8.40)	(8.44)	(8.42)
Smartdid	-0.003		-0.003
	(-1.37)		(-1.42)
Chinadid		0.003**	0.004**
		(2.47)	(2.54)
Control variables	control	control	control
Individual fixed effects	YES	YES	YES
Time fixed effect	YES	YES	YES
Constant	0.196***	0.197***	0.196***
	(9.45)	(9.51)	(9.43)
Observations	3,396	3,360	3,360
R-squared	0.636	0.637	0.637
Number of t	283	280	280
F test	0	0	0
r2_a	0.601	0.602	0.602
F	301.0	298.2	282.8

Robust t-statistics in parentheses
**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Heterogeneity Analysis

As discussed earlier, the digital economy has a considerable promotional effect on the new quality of agricultural productivity. However, differences in economic development across regions lead to varying levels of digital technology development, which, in turn, reduce the efficiency of factor allocation in agricultural production in certain areas. As a result, the level of new quality agricultural productivity may exhibit heterogeneity across regions (Myovella et al., 2020). Additionally, the core task of agriculture is to ensure national food security. The National Medium- and Long-Term Plan for Food Security (2008–2020) divides China into grain-producing regions, grain-consuming regions, and grain-producing and consuming balanced regions. Differences in agricultural production conditions and grain production priorities across regions influence the agricultural production methods and the level of emphasis placed on agriculture in those regions. Therefore, building on previous research, this study conducted a group analysis of the impact of the digital economy on agricultural productivity across different agricultural functional zones and levels of digital technology, aiming to obtain more detailed empirical results.

Heterogeneity Based on Agricultural Functional Zoning

The stable supply of grain and other important agricultural products helps address the tightening constraints on domestic arable land resources and the rapid growth in grain demand. This study explores the impact of the digital economy on the new productive forces of agriculture in different functional zones, promoting the efficient allocation of agricultural production factors and adjustments to the production structure. Based on the characteristics of grain production and consumption, China has divided the country into grain-producing regions, grain-consuming regions, and balanced grain-producing and consuming regions. This study conducted group tests across different agricultural functional zones to analyze whether the impact of the digital economy on the development of new-type agricultural productivity varies across these zones. As shown in Table 9, in grain-producing regions and in balanced grain-producing and consuming regions, the digital economy significantly promotes the development of new agricultural productivity, with significance at the 1% confidence level. In grain-consuming regions, the digital economy also promotes the development of new agricultural productivity, but the effect is not significant. This study argues that grain-producing regions, due to their regional endowment advantages, have long borne the heavy responsibility of grain production and supply, playing a pivotal role in ensuring national food security. The digital economy paradigm enhances the efficiency and quality of crop production by accelerating agricultural production reforms, promoting agricultural operational innovation, and strengthening the integration of agriculture with other industries, thereby considerably boosting productivity in grain-producing regions. By contrast, grain-producing and consuming regions prioritize a "self-sufficient" production model to meet the local population's rigid grain demand. Under the digital economy, the use of digital technology to intelligentize and enhance the efficiency of agricultural production helps farmers make more precise planting decisions, thereby stabilizing agricultural productivity, increasing grain output and quality, balancing regional grain supply and demand, and regulating the grain market. Most grain-consuming regions are economically developed and densely populated and lack the land resources required for large-scale agricultural production, making it difficult to meet local residents' grain needs. They often rely on external grain supplies. While the digital economy has boosted agricultural productivity in these regions, factors such as uneven land quality and high labor costs have prevented this effect from reaching statistical significance.

Table 9. Heterogeneity Test (1): Heterogeneity of Agricultural Functional Zones

VARIABLES	Major grain-producing areas	Major grain-consuming region	Grain production and marketing balance area
	(1)	(2)	(3)
	ANQP	*ANQP*	*ANQP*
Digit	0.116***	0.041	0.086***
	(6.81)	(1.27)	(3.87)
Constant	0.224***	0.192**	0.132***
	(6.82)	(2.51)	(5.14)
Control variables	control	control	control
Individual fixed effects	YES	YES	YES
Time fixed effect	YES	YES	YES
Observations	2,028	552	816
R-squared	0.628	0.724	0.636
Number of t	169	46	68
F test	0	0	0
r2_a	0.590	0.689	0.594
F	182.6	75.54	75.11

Robust t-statistics in parentheses
**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Heterogeneity From the Perspective of Digital Technology Levels in Various Cities

The application of digital technology has expanded farmers' access to market information, remarkably promoting agricultural production efficiency, resource management, and technological innovation. This study used internet penetration rates to measure a city's level of digital development. The sample was divided into two groups—high internet penetration and low internet penetration—based on the median internet penetration rate for regression analysis. The regression results are shown in Table 10, Columns (1) - (2). The results indicate that in cities with higher internet penetration, the digital economy remarkably promotes the development of new-quality agricultural productivity. However, in cities with lower internet penetration, the promotional effect of the digital economy on new-quality agricultural productivity is slightly lower than in cities with higher internet penetration. This study argues that regions with lower digital technology adoption rely more on traditional production methods, resulting in considerably lower efficiency than cities that use smart agricultural machinery and data analysis. This result severely limits the development of new-quality agricultural productivity. Similarly, regions lacking advanced technology cannot swiftly perceive changes in market information trends, leading to blind and inefficient agricultural production, which is detrimental to the development of new-quality productivity.

Furthermore, China's National Big Data Comprehensive Experimental Zones are special regions established by the government to develop the big data industry vigorously and promote economic transformation and upgrading. The establishment of these experimental zones often drives the development of big data-related industries, stimulates local employment, and boosts economic growth. Therefore, this study examined whether a city is designated as a National Big Data Comprehensive Experimental Zone to gauge its digital technology level. Group regression analysis revealed that in National Big Data Comprehensive Experimental Zones, the digital economy plays a key role in promoting the development of new-quality agricultural productivity. However, in cities outside National Big Data Comprehensive Experimental Zones, the promotional effect of the digital economy on new-quality agricultural productivity is slightly lower than in cities with higher internet penetration rates. The reason for this, according to this study, is that the establishment of national big data comprehensive pilot zones aggregates big data elements, builds a big data industry system, promotes the integration of agriculture with other industries, accelerates innovation in agricultural production methods and the application of data resources, thereby enhancing the level of new-type agricultural productivity.

Table 10. Heterogeneity Test (2): Heterogeneity in Digital Technology Levels

VARIABLES	High Internet penetration rate	Low Internet penetration	National Big Data Comprehensive Experimental Zone	Nonstate comprehensive big data experimental zone
	(1)	(2)	(3)	(4)
	ANQP	*ANQP*	*ANQP*	*ANQP*
Digit	0.110***	0.077**	0.125***	0.070***
	(3.40)	(2.58)	(3.54)	(5.19)
Constant	0.165***	0.144**	-0.033	0.225***
	(5.73)	(2.23)	(-0.37)	(10.64)
Control variables	control	control	control	control
Individual fixed effects	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Observations	1,692	1,692	572	2,824
R-squared	0.562	0.657	0.227	0.651
Number of t	207	214	81	283
F test	0	0	0	0
r2_a	0.557	0.653	0.0766	0.610
F	82.32	122.1	10.80	277.3

Robust t-statistics in parentheses
**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Further Analysis

Mechanism Analysis

In the preceding section, we discussed the substantial promotional role and heterogeneity of the digital economy in fostering new-quality agricultural productivity. However, how the digital economy can effectively empower new-quality agricultural productivity and drive its rapid development remains a question that this study explores in depth. Therefore, based on the aforementioned theoretical analysis, this study examined the mechanism by which the digital economy influences new-quality agricultural productivity from three perspectives: industrial upgrading effects, innovation-driven effects, and factor allocation effects. This study drew on existing scholarly research to establish the following mechanism testing model to examine the mechanism underlying the relationship between the digital economy and new-quality agricultural productivity (Wang et al., 2024):

$$M_{it} = \gamma_0 + \gamma_1 Digit_{it} + \gamma_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

$$ANQP_{it} = \gamma_3 + \gamma_4 M_{it} + \gamma_5 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

where M_{it} represents the mechanism variable, and the remaining variables are the same as in the previous equation.

Innovation-driven Effect

The development of the digital economy not only expands financing channels for agricultural production and innovation, providing diversified and differentiated capital allocation to promote agricultural production innovation, but also reduces financing costs through market-based allocation and digital platforms, alleviating issues such as backward agricultural production and insufficient innovation. This effect, in turn, enhances agricultural production efficiency and improves agricultural production methods. Therefore, this study used the number of new enterprises per 100 people to measure the region's innovation level (Gaglio et al., 2022). Innovation-driven Mechanism. As shown in Table 11, Columns (1) - (2), empirical tests reveal that the digital economy considerably drives scientific and technological innovation in the region, and this level of innovation promotes the development of new agricultural productivity. This result indicates that the digital economy effectively drives production innovation, alleviates potential "financial exclusion issues" in rural areas, and thereby promotes the development of new agricultural productivity in the region.

Factor Allocation Effect

Based on the preceding analysis, the digital economy drives the integration of capital, talent, technology, and information through data platforms and other technologies, thereby enabling the rational allocation of agricultural production factors. It also reduces labor and other factor search costs, alleviates mismatches in agricultural production factors, and enhances production efficiency. Therefore, this study uses the labor mismatch coefficient to represent factor allocation (Guvenen et al., 2020). The results of the factor allocation mechanism are shown in Columns (3) - (4) of Table 11. Empirical tests reveal that the digital economy alleviates labor mismatch, and the correlation coefficient between labor mismatch and agricultural new-quality productive capacity is negative. This result indicates that the digital economy alleviates labor mismatches through effective factor allocation, thereby enhancing agricultural production efficiency and promoting the development of new-quality productive capacity in agriculture.

Industrial Upgrading Effect

The industrial structure often reflects the distribution of resources across various sectors. The higher the proportion of the industrial structure, the more it tends toward emerging industries, leading to stronger application of science and technology, higher levels of economic modernization, and, in agriculture, improved labor efficiency and rational resource allocation. In the context of the digital economy, big data platforms and smart agricultural analysis are reshaping agricultural production and sales methods by aggregating various digital elements, such as population, capital, and knowledge. This process leverages local agricultural resources and products to foster emerging industries such as e-commerce and logistics, driving the transformation of agriculture from traditional, single-focused production to diversified, integrated development and upgrading. This upgrade enhances agricultural production efficiency, accelerates the integration of the agricultural industrial chain, and promotes the development of new agricultural productive forces. On this basis, this study used the ratio of tertiary industry value added to secondary industry value added to represent industrial upgrading (Muhammad et al., 2022). The results of the industrial upgrading mechanism are shown in Table 11, Columns (5) - (6). The digital economy has a considerable promotional effect on industrial upgrading, and industrial upgrading has a considerable promotional effect on the new quality of agricultural productivity. This finding indicates that the digital economy effectively drives the upgrading of the agricultural industrial system. Through digital technologies such as cloud computing and big data search functions provided by the digital economy, the digital economy accelerates the integration of the agricultural industrial chain and guides more effective allocation of agricultural resources, thereby enhancing the new quality of productivity.

Table 11. Mechanism Verification

VARIABLES	Innovation-driven effect		Factor allocation effect		Industrial upgrading effect	
	(1)	(2)	(3)	(4)	(5)	(6)
	Corpora	*ANQP*	*Labor*	*ANQP*	*Indusup*	*ANQP*
Digit	0.977*		-1.714*		0.024*	
	(1.87)		(-1.94)		(1.80)	
Corpora		0.001*				
		(1.88)				
Labor				-0.001*		
				(-1.68)		
Indusup						0.104***
						(5.20)
Control variables	control	control	control	control	control	control
Individual fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Constant	-2.648	0.256***	-4.339**	-0.170***	0.498***	-0.247***
	(-1.38)	(9.38)	(-2.28)	(-9.33)	(27.46)	(-11.44)
Observations	3,396	3,396	3,396	3,396	3,396	3,396
R-squared	0.319	0.668	0.022	0.511	0.178	0.441
Number of t	283	283	283	283	283	283
F test	0	0	0.0189	0	0	0
r2_a	0.316	0.666	0.0203	0.461	0.0948	0.384
F	39.70	171.6	2.581	491.4	153.0	556.5

Robust t-statistics in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Modulating Effects

Effective Government Investment

The level of government investment directly impacts the quality of agricultural infrastructure development, influences the production vitality and creativity of agricultural entities, and determines the intrinsic driving force behind rural village construction and high-quality development. Effective government investment supports economic development in underdeveloped regions, narrowing the wealth gap to some extent, while guiding agricultural resources toward key areas and high-quality industries, thereby promoting efficient allocation. Therefore, to identify the regulatory mechanisms of rural capital investment in the development of new agricultural productive forces in the digital economy, this study used the ratio of fixed-asset investment to general government fiscal expenditures as a proxy for government investment levels and constructed an interaction term between the digital economy and rural capital investment for regression analysis.

$$ANQP_{it} = \gamma_0 + \gamma_1 Digit_{it} + \gamma_2 x_{it} + \gamma_3 Digit_{it} x_{it} + \gamma_c X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

where x_{it} represents the mechanism variable, $Digit_{it}x_{it}$ represents the cross term between the mechanism variable and the digital economy, and the remaining variables are the same as in the previous equation.

As shown in Table 12, Columns (1) - (2), the interaction term coefficients are remarkably greater than 0, indicating that government investment plays a significant positive moderating role in promoting the development of new agricultural productive forces in the digital economy. This study argues that an increase in effective government investment will greatly promote the development of high-tech industries, improve agricultural production efficiency through enhanced agricultural infrastructure and agricultural production reforms, accelerate the effective integration of digital technology with agriculture and rural areas, and thereby cultivate new agricultural productive forces.

Rural Human Resource Adjustment

The application of emerging technologies and concepts relies heavily on local agricultural technical talent. Rural talent with stronger digital skills, higher-quality capabilities, and broader market access are better equipped to manage agricultural production and expand agricultural business models (Mishara, 2021). To identify the regulatory mechanisms of rural human capital in the development of new agricultural productivity driven by the digital economy, this study constructed an interaction term between the digital economy and rural human capital for regression analysis. This study used the ratio of undergraduate and vocational college students to the prefecture-level city's total population to represent the level of human capital (Liu et al., 2021). Based on the actual needs of this study, this value was multiplied by the ratio of the rural population to the prefecture-level city's total population to measure the level of rural human capital. The results are shown in Table 12, Columns (3) - (4). The interaction term coefficient is remarkably positive, indicating that in cities with stronger rural human capital, the digital economy has a stronger promotional effect on the development of new-type agricultural productivity. This study argues that rural areas with higher human capital are more inclined to optimize rural industrial structures, adopt agricultural technological innovations, and expand market sales channels. This finding not only drives surrounding farmers to collectively improve their production skills and achieve comprehensive development of laborers, but also enhances agricultural production efficiency and quality, thereby facilitating the development of new-quality agricultural productivity.

Table 12. Moderation Effects

VARIABLES	Effective government investment		Rural human capital	
	(1)	(2)	(3)	(4)
	ANQP	*ANQP*	*ANQP*	*ANQP*
Digit	0.103***	0.063***	0.106***	0.039***
	(8.20)	(3.91)	(8.39)	(2.74)
Invest	-0.001***	-0.003***		
	(-3.55)	(-5.08)		
*Digit*Invest*		0.005***		
		(4.10)		
Peo			-0.013	-0.762***
			(-0.17)	(-6.81)
*Digit*Peo*				2.361***
				(9.14)
Control variables	control	control	control	control
Individual fixed effects	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Constant	0.183***	0.191***	0.198***	0.217***
	(8.67)	(9.06)	(9.52)	(10.54)
Observations	3,396	3,396	3,396	3,396
R-squared	0.638	0.640	0.636	0.646

Number of t	283	283	283	283
F test	0	0	0	0
r2_a	0.603	0.605	0.601	0.611
F	302.6	289.0	300.7	296.9

Robust t-statistics in parentheses
**** p < 0.01, ** p < 0.05, * p < 0.1*

Expanded Analysis

After conducting an in-depth examination of the role of the digital economy in enhancing agricultural productivity and whether this role is facilitated through specific mechanisms and regulatory effects, this study deemed it necessary to revisit the topic from the perspective of e-commerce. The reason is that e-commerce is a key element in the development and expansion of the digital economy and a powerful tool for China to promote industrial digitization and drive the development of the digital industry (Shi & Wei, 2024), possesses unique commercial logic and market mechanisms that can help us more accurately reveal how the digital economy promotes transformation and upgrading by altering traditional circulation models (Sturgeon, 2021). Especially in agriculture, e-commerce promotes high-quality agricultural products through branding strategies, stimulates industrial cluster effects, forms advanced, modernized, and integrated production chains, effectively reshapes the industrial structure of agricultural regions, improves labor productivity, and enhances the competitiveness of agricultural specialty industries. Additionally, leveraging the radiating and driving effects of digitalization, China's National E-commerce Demonstration City initiative proactively guides the flow of production factors and e-commerce talent to rural areas, promoting multifactor input guarantees and multistakeholder collaboration to alleviate funding constraints and technological lag in agricultural production (Liu et al., 2025). Therefore, this study re-examined the impact of the digital economy on the new productive forces in agriculture from the perspective of national e-commerce demonstration city pilot policies and rural e-commerce. This re-examination not only fills research gaps but also provides decision-making references for policymakers and businesses, comprehensively examining the specific impact of the digital economy on the new productive forces in agriculture.

To examine whether national e-commerce demonstration cities drive the development of new agricultural productivity in the context of the digital economy, this study combined existing research with a quasi-natural experiment based on the construction of national e-commerce demonstration cities to explore the impact of this policy on the development of new agricultural productivity (Zhong *et al.*, 2024). This study constructed a two-way fixed multiperiod DID model, as shown in Equation (5), to test the policy effects of the national e-commerce demonstration city policy on agricultural new-type productive capacity. Among them, ANQP is the dependent variable, representing the level of agricultural new-type productive capacity in each prefecture-level city; DID is the core explanatory variable, representing the national e-commerce demonstration city policy. In the model, $DID_{it} = Post_t \times Treat_i$. In variable $Treat_i$, sample cities that implemented the national e-commerce demonstration city policy are assigned to the treatment group, with $Treat_i$ valued at 1, while others are assigned to the control group, with $Treat_i$ valued at 0. Additionally, when a city implements the national e-commerce demonstration city policy in year t, $Post_t$ is valued at 1, while previous years and cities that did not implement the policy are valued at 0. In 2011, China implemented the national e-commerce demonstration city pilot policy in 23 cities, including Beijing and Tianjin. In 2014, 30 cities, including Yiwu and Quanzhou, were designated as national e-commerce demonstration cities. In 2017, the National Development and Reform Commission launched the third batch of national e-commerce demonstration city policies in 17 cities, including Dalian and Baotou. The estimated value of the coefficient γ_2 reflects the direction and extent of the impact of the national e-commerce demonstration city policy on agricultural new productive capacity. Additionally, X_{it} represents the control variable group, λ_i and δ_t reflect individual and year fixed effects, respectively; μ_{it} is the random disturbance term.

$$ANQP_{it} = \beta_2 + \gamma_2 DID_{it} + \varphi_2 X_{it} + \lambda_i + \delta_t + \mu_{it} \tag{6}$$

Table 13 presents the corresponding regression results. The findings indicate that the regression coefficient for the core explanatory variable, DID, is significantly positive, suggesting that, in the context of the digital economy, the national e-commerce demonstration city pilot policy continues to play a promotional role in fostering new-quality agricultural productivity. This finding implies that after the policy is implemented, the construction of e-commerce demonstration cities is more conducive to the digital economy, providing a driving force and thereby promoting the development of new-quality agricultural productivity. The exogenous policy dummy variable mentioned earlier was added for further testing to eliminate the interference of other policies, and the results remained unchanged. This study argues that the development of rural e-commerce not only facilitates the establishment of multilevel e-commerce service platforms in rural areas and cultivates rural digital consumption scenarios to increase farmers' income but also expands agricultural information services, accelerates the upgrading of the rural industrial structure, enhances rural production efficiency and technological levels, and thus effectively promotes the development of new-type agricultural productivity.

Table 13. Extended Analysis 1: Role of National E-Commerce Demonstration City Pilot Policies in Promoting New Agricultural Productivity

VARIABLES	Benchmark regression	Broadband China	Smart City	Simultaneous control
	ANQP	*ANQP*	*ANQP*	*ANQP*
DID	0.004**	0.004**	0.005**	0.004**
	(2.23)	(1.97)	(2.39)	(2.10)
Chinadid		0.003**		0.003**
		(2.10)		(2.16)
Smartdid			-0.003*	-0.003*
			(-1.69)	(-1.71)
Control variables	control	control	control	control
Individual fixed effects	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Constant	0.236***	0.236***	0.234***	0.234***
	(11.54)	(11.51)	(11.43)	(11.40)
Observations	3,396	3,360	3,396	3,360
R-squared	0.628	0.629	0.629	0.629
Number of t	283	280	283	280
F test	0	0	0	0
r2_a	0.593	0.593	0.593	0.593
F	308.1	288.2	291.3	273.3

Robust t-statistics in parentheses
**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Furthermore, rural e-commerce has emerged as a key driver for innovative business models and accelerated market circulation under the influence of e-commerce, and it also serves as a strong foundation for promoting rural industrial transformation and boosting farmers' incomes. Since 2014, China's Central Document No. 1 has continuously planned and deployed rural e-commerce initiatives for 10 consecutive years, thereby increasing financial investment not only in building a three-tier e-commerce service system at the county, township, and village levels and in improving logistics and delivery services, but also in driving digital technology innovation. It has strengthened the comprehensive, multilevel, and full-chain integration of e-commerce with rural primary, secondary, and tertiary industries, forming a refined, data-driven, and substantive rural e-commerce ecosystem (Wu et al., 2020). Visibly, farmers utilize live-streaming platforms such as Douyin and Kuaishou, as well as e-commerce platforms such as Pinduoduo and Taobao, to sell products across regions. Local governments organize and cultivate rural brands with regional and product advantages, explore new channels for product sales and financing, and build rural e-commerce industrial clusters through upstream-downstream collaboration. Rural e-commerce not only transforms traditional rural production and sales methods, bringing new opportunities for rural economic development, but also bridges the digital divide between urban and rural areas through digital platforms, breaking down data barriers between urban and rural regions, and promoting economic development in remote agricultural and rural areas. It has already driven the digitalization, diversification, and efficiency of rural business sectors. Given the radiating and driving effects of e-commerce, will the development of rural e-commerce impact the new productive forces in agriculture? This study further explored and analyzed this question.

This study used the presence of Taobao villages in a prefecture-level city as a criterion to measure the development of rural e-commerce (Liu & Zhou, 2023) and constructed a two-way fixed multiperiod DID model, as shown in Equation (6), where TB_{it} is the core explanatory variable, with $TB_{it} = Post_t \times Treat_i$. In variable $Treat_i$, if a sample city has a Taobao Village, it is assigned to the treatment group, with $Treat_i$ valued as 1; otherwise, it is assigned to the control group, with $Treat_i$ valued as 0. Additionally, if a city has a Taobao Village in year t, $Post_t$ is assigned a value of 1, while previous years and cities without Taobao villages are assigned a value of 0. All other variables are the same as above.

$$ANQP_{it} = \beta_3 + \gamma_3 TB_{it} + \varphi_3 X_{it} + \lambda_i + \delta_t + \mu_{it} \quad (7)$$

Table 14 presents the corresponding regression results. As shown in the table, the development of rural e-commerce has a considerable promotional effect on the new quality of agricultural productivity. The exogenous policy dummy variable mentioned earlier was added for further testing to eliminate the interference of other policies, and the results remained unchanged. This study argues that rural e-commerce provides convenient and efficient market distribution channels for agricultural products, optimizes and upgrades the product production chain, and facilitates the upgrading and advanced development of the agricultural industrial structure, thereby injecting new momentum into the new quality of agricultural productivity.

Table 14. Extended Analysis 2: Role of Rural E-commerce in Promoting New Agricultural Productivity

VARIABLES	Benchmark regression	Broadband China	Smart City	Simultaneous control
	ANQP	*ANQP*	*ANQP*	*ANQP*
TB	0.003**	0.002*	0.003**	0.002*
	(2.12)	(1.85)	(2.13)	(1.85)
Smartdid			-0.003	-0.003*
			(-1.62)	(-1.68)
Chinadid		0.004**		0.004**
		(2.46)		(2.55)
Control variables	control	control	control	control
Individual fixed effects	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Constant	0.178***	0.177***	0.178***	0.177***
	(45.39)	(45.14)	(45.41)	(45.16)
Observations	3,396	3,360	3,396	3,360
R-squared	0.621	0.622	0.622	0.622
Number of t	283	280	283	280
F test	0	0	0	0
r2_a	0.585	0.585	0.585	0.586
F	363.2	335.9	339.3	315.2

Robust t-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Practical Difficulties

The digital economy provides abundant digital resources and broad application scenarios, making it a routine means for increasing agricultural productivity. Based on the benchmark regression analysis and mechanism analysis mentioned above, this study combines the current state of China's digital economy development and proposes the following three practical challenges for the digital economy's empowerment of new agricultural productivity.

Agricultural Digital Infrastructure Development Lags Behind Actual Needs

Empirical analysis shows that the promotional effect of the digital economy on agricultural productivity is more pronounced in regions with higher digital technology penetration, while its impact is weaker in remote, technologically underdeveloped areas. This finding indicates that the differentiated development of digital infrastructure directly influences the effectiveness of the digital economy's enabling role. The development of the digital economy primarily relies on the data-driven creativity enabled by digital infrastructure development. The quality of agricultural data is closely related to the effectiveness of the digital economy's application in the agricultural sector, influencing the vitality and creativity of various market entities in agriculture and determining the intrinsic driving force behind the development of new agricultural productivity. However, given the incomplete infrastructure coverage in China, the 53rd "Statistical Report on the Development of China's Internet" indicates that the informatization rate of agricultural production has only reached 25%. As of 2023, the internet penetration rate in rural China was only 66.5%, indicating insufficient investment in agricultural infrastructure construction. Digital infrastructure, such as broadband networks and mobile communication base stations, cannot be fully deployed in remote areas, and the current funding level cannot meet the actual needs of agriculture, leading to insufficient or lagging agricultural internet infrastructure construction, which restricts the application and promotion of digital technology (Zou et al., 2022). In particular, the supply–demand matching mechanism for rural digital infrastructure construction is not yet established. In practice, research on the actual needs of grassroots agricultural levels is lacking, and the compatibility of different digital infrastructure designs has not been considered. Moreover, unified standards and planning are lacking, leading to resource waste and low efficiency (Meng et al., 2023). Additionally, the effects of the digital economy on agriculture vary regionally, with the digital divide becoming increasingly evident across regions. In remote and resource-scarce areas, the lack of digital infrastructure prevents the interoperability of multiscenario data, hindering the effective integration and sharing of agricultural data. This lack of infrastructure impedes the inclusive, interconnected, and foundational functions of digital infrastructure development, obstructs the promotion of data-driven production management methods, and ultimately limits the development space for new agricultural productivity (Peng & Dan, 2023).

Mismatch Between the Agricultural Industrial Structure Chain and Production Factors

In-depth exploration of the profound transformation and upgrading of the agricultural industrial structure and the allocation of factors has become a key focus and convergence point for shaping the new productive forces of agriculture. The digital economy can promote the new quality of agricultural productivity through industrial upgrading effects, but this effect is limited in regions with incomplete agricultural industrial chains. Even if provinces strengthen support for advantageous and distinctive industries, the lagging agricultural industrial structure will still hinder improvements in agricultural total factor productivity, thereby affecting the development of a new quality of agricultural productivity (Zhang et al., 2022). On the one hand, the upgrading of the agricultural industrial structure essentially drives the process of new quality momentum factors aggregating toward efficient industries. However, China's agricultural industrial chains often suffer from disconnections or gaps, with ineffective coordination among the production, processing, sales, and service segments. This issue prevents production factors from being effectively allocated to secondary and tertiary industries or to advantageous primary industries, limiting the digital economy's ability to fully realize its potential across the entire industrial chain (Hao et al., 2023). On the other hand, the integration and application of digital technologies in agricultural production remain low, and the standardization of agricultural production is generally inadequate. Many stages still rely on traditional production methods. Barriers to the flow of agricultural production factors across regions and industries exist, and the digital economy must overcome them to integrate resources effectively. However, these barriers are difficult to eliminate in the short term (Abiri et al., 2023).

Insufficient Scientific and Technological Innovation Hinders Agricultural Scientific Research Promotion and Application Supply

This study empirically finds that the digital economy stimulates innovation-driven effects by expanding financing channels, effectively empowering the new productive forces of agriculture. However, in reality, traditional technologies struggle to meet the growing demands of agricultural production effectively. Technology innovation driven by entrenched experience has, to some extent, hindered the development of agricultural operations. Insufficient scientific and technological innovation remains a limiting factor in enhancing the quality and efficiency of agricultural productivity (Patel et al., 2020). In recent years, according to reports by the People's Daily, China's contribution rate to agricultural science and technology has increased from 54.58% in 2012 to over 63% in 2024. However, compared with developed countries, a substantial gap persists, and the challenge of effectively translating scientific and technological innovation into practical agricultural needs has not been fundamentally resolved. The reasons for this are twofold. On the one hand, the agricultural innovation field is theory-oriented and ignores actual production needs, resulting in a disconnect between research results and production needs and making it difficult to translate them into increased productivity (Rose et al., 2021). In particular, Chinese agricultural research mainly relies on the National Natural Science Foundation, and scientific research and innovation are mainly based on laboratory research. When converting to field trials, factors such as temperature, light, and unexpected weather must be considered. On the other hand, China's agricultural technology promotion system is incomplete, making it difficult for agricultural innovation technologies to find effective channels and mechanisms for promotion, thereby hindering the rapid dissemination of scientific and technological innovation achievements to the front lines of agricultural production (Yu et al., 2020). In particular, agricultural, scientific, and technological innovation requires substantial financial investment, yet in reality, it often faces funding shortages, limiting the depth and breadth of research.

Discussion

First, the promotional effect of the digital economy on agricultural productivity is not "automatically effective" and is subject to contextual dependence and institutional constraints. The empirical results of this study support the remarkable enhancement of agricultural productivity by the digital economy, but the mechanism analysis and heterogeneity tests suggest that this promotional effect is more pronounced in regions with high digital technology penetration, where agriculture is primarily focused on production zones or production–sales balanced zones, and where factor allocation is relatively smooth. This finding implies that the mere construction of digital infrastructure and the introduction of digital tools cannot guarantee a comprehensive enhancement of agricultural productivity. According to the theory of technology adoption and diffusion, even if digital tools possess advanced functionality, if agricultural entities lack perceptions of usefulness or ease of use or lack matching organizational support, the adoption and diffusion of technology may remain at a superficial application level, making it difficult to form a data-driven, systematic production model (Caffaro et al., 2020). From the perspective of ROT, the potential of the digital economy can only be fully realized when data, capital, and human resources form effective synergy across the three stages of acquisition, integration, and utilization (Zhou et al., 2024). Therefore, the positive effects of the digital economy are not "plug-and-play" but rather depend on multiple conditions, such as technological adoption willingness, talent reserves, and factor integration efficiency. This conclusion suggests that policy formulation and practice promotion should not only focus on expanding the quantity of digital infrastructure but also prioritize optimizing "soft conditions," such as farmers' digital literacy and the development of cross-departmental collaboration platforms.

Second, heterogeneous results indicate that the spatial distribution of the digital economy's empowerment of agriculture is uneven, reflecting differences in agricultural functional positioning, technological endowments, and industrial foundations. This study finds that in grain-producing regions and regions with balanced production and sales, the digital economy has a greater impact on promoting new agricultural productivity, whereas this effect is not significant in major consumption regions. This outcome is partly related to factors such as arable land resources, labor costs, and the completeness of the industrial chain. By contrast, it reflects the differing operational models of the digital economy across different functional zones (Miao et al., 2021): in major production areas, it primarily enhances output and quality through means such as intelligent production and precision agriculture; in major consumption areas, where agricultural scale is constrained, investments in the digital economy struggle to generate sufficient output spillover effects. Similarly, the level of technological advancement directly impacts the intensity of empowerment. Regions with high digital tool adoption rates can quickly integrate these tools across the entire supply chain, whereas regions with low adoption rates may face a disconnect between infrastructure and applications (Bejlegaard et al., 2021). This finding suggests that digital economy empowerment requires tailored spatial strategies rather than a one-size-fits-all approach.

Third, mechanism analysis reveals that the enabling pathways of the digital economy are diverse, but each mechanism's effectiveness is constrained by resource and institutional environments. This study validates the mediating roles of industrial upgrading effects, factor allocation effects, and innovation-driven effects, all of which significantly and positively influence the new quality of agricultural productivity. However, the dominance of different mechanisms may vary across regions and stages: in regions with short industrial chains or weak processing sectors, industrial upgrading pathways may be constrained; in regions with underdeveloped factor markets or low factor mobility, the factor allocation effect may not be fully realized; and in regions with insufficient innovation investment or an incomplete technology dissemination system, the sustainability of the innovation-driven effect may also be challenged. This finding implies that promoting the digital economy’s empowerment of agricultural new-quality productive capacity should not rely on a single pathway but should instead develop differentiated empowerment strategies based on local industrial maturity, factor mobility, and the robustness of the innovation system (Ye, 2025).

Fourth, the results of the moderation effect analysis indicate that government-led effective investment and rural human capital are not only external support conditions but also act as “multipliers” that amplify the impact of the digital economy. Government investment can accelerate technology adoption by improving hardware infrastructure (such as network towers and smart agricultural machinery) and optimizing software services (such as agricultural data platforms and digital finance), thereby shortening the time from investment to output. Rural human capital directly influences the speed and depth of technology adoption, with highly skilled labor capable of transforming digital tools into actual productive capacity. However, this also highlights a potential risk: in regions with insufficient investment or weak human capital, even if the level of digital economic development improves, the conversion rate to new agricultural productivity will remain considerably low and even lead to “digital idling.” Therefore, at the policy level, hardware construction and human capital development should be advanced simultaneously to avoid imbalances such as “prioritizing equipment over talent” or “prioritizing platforms over applications” (Sairmaly, 2023).

Fifth, the significant positive effects of rural e-commerce and national e-commerce demonstration city policies in the expanded analysis further illustrate that the empowerment of the digital economy not only relies on the digitization of the production process but also requires the formation of a closed loop in the circulation and market segments. Rural e-commerce breaks down information barriers, expands sales channels, and extends the industrial chain, not only directly increasing the added value of agricultural products but also driving the digital upgrading of the production end (Chen & Long, 2024). However, its sustainability still depends on brand building, logistics systems, and the cultivation of e-commerce talent (Sarkar et al., 2024). If the e-commerce model cannot be deeply integrated with local specialty industries or remains stuck in low-price competition and traffic-driven stages, its role in enhancing agricultural productivity may be difficult to sustain in the long term.

Conclusions and Implications

Conclusions

This study is based on panel data from 283 prefecture-level cities from 2011 to 2022 and constructs a “technology adoption–resource allocation” dual-path mechanism framework. It measures agricultural new-quality productivity from three dimensions: agricultural new-quality laborers, agricultural new-quality labor materials, and agricultural new-quality labor objects. It systematically examines the impact and mechanisms of the digital economy on new-type agricultural productivity and introduces the moderating effects of government-effective investment and rural human capital to further analyze the enabling role of rural e-commerce and the national e-commerce demonstration city pilot policy. The main research conclusions are as follows:

(1) The digital economy remarkably promotes the development of new agricultural productivity. Empirical results show that, regardless of whether regional macroeconomic and social development differences are controlled for, the digital economy has a positive effect on new agricultural productivity at the 1% significance level, and this conclusion holds across various robustness tests. For every 1 percentage point increase in the digital economy, new agricultural productivity increases by an average of approximately 0.11 percentage points.

(2) The enabling role of the digital economy exhibits considerable regional heterogeneity. In major grain-producing regions, regions with balanced grain production and consumption, areas with high digital technology penetration rates, and national big data comprehensive pilot zones, the digital economy plays a more pronounced role in promoting new agricultural productivity. However, in major grain-consuming regions and areas with lower

levels of digital technology, this role is either insignificant or weak, reflecting the differential impacts of technological, industrial, and agricultural functional endowment positioning.

(3) The effects of industrial upgrading, factor allocation, and innovation-driven development are key mechanisms through which the digital economy empowers new agricultural productivity. The digital economy promotes the deep integration of agriculture with the secondary and tertiary industries, optimizes the dynamic allocation of land, labor, capital, and technology, and enhances scientific research and management innovation capabilities, thereby achieving coordinated improvements in agricultural production efficiency, green development, and technological content.

(4) Effective government investment and rural human capital have a significant positive regulatory effect on the digital economy's empowerment of new agricultural productivity. Government investment can improve hardware facilities and supporting services, and accelerate the implementation and transformation of technology. Rural human capital, by contrast, can amplify the productivity transformation effects of the digital economy by accelerating and deepening digital technology adoption.

(5) Rural e-commerce and the national e-commerce demonstration city pilot policies have remarkably enhanced the new productive forces in agriculture. The development of e-commerce has played an important role in optimizing agricultural product distribution channels, extending industrial chains, enhancing market feedback, and brand building, forming a virtuous cycle of digitalization at the production end and marketization at the distribution end, and further unleashing the potential of the digital economy in the agricultural sector.

Policy Implications

The conclusions of this study have the following policy implications:

(1) Implement targeted policies to promote the deep integration of the digital economy and agriculture and narrow regional development gaps. Given that the digital economy plays a more considerable role in promoting new agricultural productivity in major grain-producing regions, regions with balanced production and sales, and areas with high digital technology penetration, central and local governments must implement differentiated digital development strategies in agricultural functional zones. In major production areas, the focus should be on deploying intelligent agricultural machinery, precision farming, and agricultural big data platforms; in major consumption areas, efforts should be made to cultivate urban-style modern agriculture, agricultural product processing, and digital supply chain systems; in regions with lower digital technology levels, priority should be given to addressing shortcomings in information infrastructure to ensure the foundational conditions for digital empowerment.

(2) With a focus on a dual-path approach of "technology adoption + resource allocation," the support system for agricultural digitization should be improved. Policy design should simultaneously focus on farmers' and agricultural entities' technical adoption capabilities (cognitive, skill-based, and usability-related) and the dynamic integration capabilities of various production factors (capital, land, labor, and data). In terms of technology adoption, initiatives such as digital literacy training, promotion of demonstration applications, and socialized technical services can be implemented. Regarding resource orchestration, a cross-departmental, cross-industry agricultural digitalization collaboration platform should be established to achieve data interoperability and to efficiently allocate production factors across the research, production, and distribution stages.

(3) The dual-drive model of effective government investment and rural human capital development must be strengthened to amplify the transformative effects of the digital economy. Government investment should prioritize hardware infrastructure, such as broadband networks, smart agricultural machinery, and agricultural IoT, as well as software services such as agricultural data platforms and digital finance, to create a synergistic framework where hardware and software work together. At the same time, support for rural education, vocational training, and the popularization of digital skills should be increased to enhance the quantity and quality of rural human capital, ensuring that digital technologies can be effectively utilized in production practices.

(4) Rural e-commerce should be used as a lever to connect the production end and the market end in a digital closed loop. The construction of national e-commerce demonstration cities should be promoted in more regions, and rural areas should be encouraged to develop multilevel e-commerce service platforms and local specialty brands. By improving the rural logistics and distribution network, cultivating e-commerce operation talent, and strengthening brand building, the empowerment of the digital economy can be extended to the circulation and marketing of agricultural products, achieving mutual promotion and progress between production digitization and market digitization, and driving the extension of the agricultural industry chain and the upgrading of the value chain.

(5) Existing bottlenecks must be addressed by implementing chain-complementing, chain-strengthening, and chain-extending initiatives to unlock the potential of the digital economy. To address issues such as lagging agricultural digital infrastructure, incomplete industrial chains, and insufficient scientific and technological innovation, a standardized system for agricultural digital infrastructure should be established to promote standardization and digital transformation across all links of the industrial chain. Mechanisms for converting agricultural, scientific, and technological achievements should be improved, and joint research and development efforts among industry, academia, and research institutions, as well as field trials and promotion, should be

supported. Additionally, through fiscal incentives and risk compensation measures, social capital must be attracted to invest in agricultural innovation and digitalization projects, fostering long-term, stable technological supply and iterative capabilities.

Limitations and Future Directions

This study also has certain limitations and room for improvement: (1) Limitations in the scope of the sample and indicators. The sample time range for this study is 2011 - 2021, covering the initial stages, rapid development, and partial implementation of policies related to China's digital economy. However, the interaction between the digital economy and agricultural new-quality productivity may exhibit strong dynamics and long-term effects, such as lagged technology diffusion and the gradual release of policy benefits. Short- and medium-term panel data may struggle to fully capture these long-term changes. Additionally, some core variables (such as the agricultural new-quality productivity index and the digital economy development index) are constructed using existing statistical definitions and entropy-weighting methods. Given data availability constraints, certain subdimensions (such as real-time data collection capabilities in agricultural production processes and the depth of digital technology application) cannot be fully incorporated into the measurement, potentially leading to biases in the indicators' depiction of real differences between regions. In the future, the timeliness and granularity of measurements can be improved by extending the observation period, introducing updated statistical criteria, or utilizing new data sources such as remote sensing and the IoT. (2) Insufficient depth of mechanism identification. Although this study verifies the intermediary pathways through which the digital economy empowers new-quality agricultural productivity via industrial upgrading effects, factor allocation effects, and innovation-driven effects, it lacks a more detailed depiction of the micro-level transmission chains within these mechanisms. For example, in the industrial upgrading effect, different types of digital technologies (such as AI, blockchain, and IoT) may penetrate different stages of primary production, processing, and sales to varying degrees; in the factor allocation effect, the flow of factors such as land, labor, capital, and data is constrained by multiple factors including institutional, market, and spatial distance, and their interactive impacts require more detailed identification. In the future, combining farmer survey data, enterprise operational data, or multilevel input–output tables could enable a more in-depth characterization of the differences in digital technology types and factor mobility mechanisms, thereby enhancing the explanatory power of the mechanism.

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