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Empowering food security through digital villages: mechanisms, regional heterogeneity and policy insights from China

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Introduction: Food security constitutes a fundamental pillar of national development. Digital-village construction (DVC) plays a critical role in enhancing food security levels (FSL), yet the full scope of its impacts has not been comprehensively examined.
Methods: This study uses panel data from 31 Chinese provinces from 2011 to 2023 and employs a two-way fixed effects model to evaluate the effects of DVC on FSL and its spatial impacts.
Results: The results indicate that DVC significantly improves local FSL, with particularly strong effects in major grain-producing regions. However, the cross-regional spillover of these effects remains limited. The mechanism analysis shows that this effect operates through two primary channels: agricultural technology training coverage and land productivity, with government scale playing a positive moderating role.
Discussion: Based on these findings, regionally differentiated promotion mechanisms should be established. Prioritizing digital literacy cultivation, enhancing agricultural digital service capacity, improving platform-based data coordination systems, and strengthening fiscal support with performance-oriented governance are essential steps.

KEYWORDS
agricultural technology training, China, digital technology, digital-village construction, food security, land productivity

1 Introduction

The global food security issue has shifted from phase-based shortages to systemic vulnerability under multiple shocks. The Global Food Crisis Report points out that conflict, economic shocks, extreme weather, and forced displacement continue to exacerbate global food insecurity and malnutrition (FSIN, 2025). In this uncertain context, traditional factor input and expansion-based production models face limitations, and building resilience in the global food system is urgent. To address this challenge, digital transformation is often seen as an opportunity to enable sustainable futures in agriculture and rural areas (Rijswijk et al., 2021), providing support for improving the resilience of food security systems and optimizing production efficiency. However, food security systems remain constrained by traditional measurement paradigms and policy logic, and this lag is weakening their resilience. How to establish an effective connection between digital transformation and food security systems, and whether digitalization can truly enhance the security and sustainability of food systems, has become a key issue to resolve. China's practice provides a unique real-world example for this issue. As the largest developing country in the world, China has continuously promoted multiple institutional and policy explorations in agriculture and rural areas. In 2019, China proposed the implementation of the "Digital Village Strategy," becoming an important practice for the concentrated promotion of digital transformation in the agricultural and rural sectors (Zhao et al., 2022). Digital-village construction (DVC) represents a new trajectory of agricultural and rural modernization (Zeng et al., 2021), the digital technologies it deploys are widely viewed as a key driving force for improving agricultural productivity and fostering high-quality development (Xia et al., 2019). In this context, China's DVC is both a leading global experiment in digital transformation and provides an observable institutional setting to identify how digitalization enhances food security levels (FSL), offering valuable insights for other developing countries.

Existing literature has developed a substantial body of research around the two broad themes of food security and digital villages. However, studies that explicitly integrate these two strands remain relatively limited. In the field of food security research, traditional studies have predominantly focused on quantitative security, with most analyses characterizing food production conditions using single indicators such as total grain output or yield per unit area (Huang et al., 2025; Wang Z. et al., 2025; Peng and Huang, 2024). Only a small number of studies have incorporated total volume, structural balance, ecological sustainability, and quality security within a unified analytical framework (Gong and Zhang, 2023; Wang G. et al., 2025). Although existing research has expanded measurement approaches to food security, quantity-oriented perspectives continue to dominate, and a comprehensive and systematic framework has yet to be established. In addition, increasing attention has been paid to the effects of external factors such as climate change, agricultural insurance, labor prices and demographic structure, and industrial integration on food security (Campbell et al., 2016; Hou and Wang, 2025; Yang et al., 2016; Chen et al., 2025). With respect to research on digital villages, most studies have centered on the digital economy and examined its role in promoting green agriculture, farmland protection, rural industries, and common prosperity (Hong et al., 2023; Zhai et al., 2025; Jia and Zhu, 2025; Zhou et al., 2024; Lu et al., 2025). The development of the digital economy is widely regarded as a key factor in enhancing the resilience of food systems (Wang et al., 2024), while the application of digital technologies can effectively increase grain yields through improvements in service provision, field management, and agricultural mechanization (Peng and Huang, 2024). Existing studies have also confirmed the positive effects of digital industrial development and digital service capacity on agricultural ecological efficiency (Hu and Liu, 2025). Although digital approaches have demonstrated considerable potential in improving agricultural productivity and safeguarding food security, most studies remain focused on the effects of the digital economy, thereby overlooking the systemic relationship between DVC and FSL.

In summary, existing research still has three main limitations: first, most studies simplify FSL indicators to quantitative security, a single measurement approach that is insufficient for explaining the structural vulnerability of production systems in the context of digitalization. This may affect the scientific accuracy and precision of policies. Second, existing research primarily focuses on the impact of the digital economy and digital technologies on agriculture, neglecting the role of DVC from the perspective of macro-level institutions and service environments. Furthermore, some studies commonly use unified digital indicators for urban and rural areas, lacking detailed characterization of the digital features at the rural level. As a result, the dual-indicator system of DVC and FSL remains underdeveloped. Third, relevant research often stops at verifying the superficial correlation between digital technologies and food security, lacking in-depth analysis of the mechanisms, spatial effects, and regional differences between the two. The intrinsic logic of how DVC enhances FSL through infrastructure improvement and optimization of public services has yet to be fully explained.

In light of this, based on panel data from 31 provinces in China from 2011 to 2023, this paper systematically analyzes the impact of DVC on FSL and further deepens the study of its impact mechanisms, spatial effects, heterogeneity, and moderating effects. The potential contributions of this study are as follows: First, it improves the measurement system by constructing a dual-dimensional evaluation system for DVC and FSL, tailored to rural characteristics, providing a tool reference for related empirical research. Second, it deepens the mechanism analysis by breaking through the superficial analysis in existing studies, addressing the shortcomings in the literature regarding the explanation of the mechanisms of agricultural technology training coverage and land productivity. Third, from a spatial perspective, this paper identifies the spatial correlation of food security and introduces spatial econometric methods to supplement the baseline results. It further combines regional location, functional positioning, and quantile regression analysis to systematically describe the spatial differences and heterogeneity in the impact of DVC on FSL, thereby enriching the study of the boundary conditions of DVC's empowering effects. Fourth, it empirically tests the positive moderating effect of government scale, clarifying the collaborative empowerment logic between DVC and government agricultural fiscal investment, providing new empirical evidence for related fields.

The remainder of this paper is structured as follows: Section 2 constructs the theoretical analysis framework and presents the research hypotheses; Section 3 introduces the data sources and research design; Section 4 presents the empirical results and analysis; Section 5 provides an extended discussion; Section 6 discusses the research findings; Section 7 concludes with the main conclusions, policy recommendations, and a summary of the research limitations.

2 Theoretical framework and research hypotheses

In the context of digital transformation, DVC is not simply a technological investment, but rather a systematic embedding of information technologies such as big data, the Internet of Things, and artificial intelligence into agricultural production, rural life, and grassroots governance processes. It represents an important form of agricultural and rural informatization development in the new era. DVC promotes the deep integration of informational elements with traditional agricultural factors, systematically improving the technical conditions and operational environment for rural digital development. This paper systematically analyzes the impact of DVC on FSL from three perspectives: direct effects, intermediary mechanisms, and moderating effects, and proposes the research hypotheses.

2.1 The direct effect of DVC on FSL

In the context of digital transformation, DVC improves the overall security of the food system by reallocating informational elements and optimizing the institutional environment, which enhances information efficiency and the way resources are allocated, ultimately optimizing the operation logic of food production and supply systems. From the perspective of information economics, agricultural production generally suffers from information asymmetry and high information search costs, leading to distorted resource allocation and reduced production efficiency. Rural digitalization significantly improves production decision-making efficiency by reducing information acquisition and transmission costs and increasing information transparency (Aker, 2011).

First, agricultural informatization constitutes a core driving force in the evolution of modern agricultural production systems. By embedding digital technologies into production processes, it reshapes information transmission and decision making structures within agricultural production (Zhu et al., 2019; Han and Zhang, 2015). As a fundamental pillar of DVC, digital infrastructure functions not only as the physical carrier of information flows but also as a prerequisite for the integration of digital technologies into production systems. Improvements in rural network coverage, data collection terminals, and information sensing facilities enable digital technologies to be embedded throughout grain production, management, and circulation processes, facilitating a shift from experience based to data-oriented production. On the one hand, enhanced digital infrastructure substantially reduces information acquisition and transaction costs and mitigates the information asymmetry that is pervasive in agricultural production (Aker et al., 2016). This allows farmers to more promptly access information on climatic conditions, production environments, and market signals, thereby reducing uncertainty in production decisions, optimizing input allocation, and enhancing the stability and sustainability of grain production. On the other hand, the integration of digital technologies into production processes under improved infrastructure conditions increases precision and controllability, reduces resource waste and environmental pressure, and improves the stability of grain output while simultaneously accounting for ecological constraints and structural coordination.

Second, building upon the strengthened technical foundation provided by digital infrastructure, DVC further promotes FSL through digital services. Grain production inherently relies on the input of key factors, including labor, capital, and technology. By leveraging the inclusive effects of digital technologies, DVC expands access to credit resources and information channels for small scale producers (Yi, 2021), enabling farmers to dynamically adjust input structures during the production process, enhance their capacity to respond to external shocks, and improve the stability of the grain production system. Capital constitutes a critical support for grain production activities, and digital inclusive finance alleviates financing constraints faced by farmers by virtue of its digital and inclusive characteristics, thereby effectively safeguarding food security (Lin et al., 2022). Technology represents another important driving force, as agricultural technological innovation accelerates the transition toward green agricultural development, promotes resource saving and environmentally friendly production, and enhances the ecological security of grain production (Zhang et al., 2022). Through information feedback and service coordination mechanisms, digital services guide the rational allocation of production factors, mitigate risks of structural imbalance, and strengthen the overall resilience of the food system.

Taken together, DVC can reinforce FSL through a mechanism chain encompassing information efficiency enhancement, factor optimization, and improvements in system resilience. Accordingly, Hypothesis 1 is proposed.

> *H1*: DVC has a significant positive effect on FSL.

2.2 Indirect effects of DVC on FSL

DVC not only exerts a direct effect on FSL but also generates indirect effects by alleviating key constraints in grain production. In the production process, the achievement of FSL is often jointly constrained by technological limitations arising from insufficient farmers' capacity to absorb technology and by factor constraints resulting from low efficiency in land factor allocation. By improving the information environment and the conditions for digital technology development, DVC provides critical support for relaxing these constraints. Based on this logic, this paper selects agricultural technology training coverage and land productivity as mediating variables to characterize the transmission pathways through which DVC influences FSL by easing technological and factor constraints.

First, by integrating information platforms with educational systems, DVC enhances both the breadth and effectiveness of agricultural technology training, thereby alleviating technological constraints in grain production. According to information economics theory, the diffusion of the internet facilitates information exchange among governments, research institutions, and social organizations, improving the efficiency of knowledge dissemination (Jiang et al., 2021). However, in developing countries, farmers commonly face knowledge gaps, particularly in pesticide application and pest and disease identification, and grain production decisions often rely on experience based judgment (Li et al., 2017; Khan and Damalas, 2015; Zhu et al., 2014), which increases production risk. Although agricultural information infrastructure has continued to improve, disparities persist in farmers' capacity to access and utilize information, especially among emerging agricultural operators (Ruan et al., 2017). Farmer behavior theory suggests that technology adoption is primarily driven by expected benefit maximization, while the positive externalities associated with the digital attributes of DVC improve the decision environment for technology adoption by reducing information search costs and replication costs (Goldfarb and Tucker, 2019). Digital platforms not only lower training costs but also enable more precise matching of technical guidance. Existing studies show that improvements in farmers' digital literacy significantly strengthen their sustainable cultivation practices (Liu et al., 2025). Taken together, DVC mitigates technological constraints in grain production by expanding agricultural technology training coverage, thereby enhancing FSL.

Second, DVC alleviates factor constraints in grain production by promoting the flow and intensive utilization of land factors, thereby improving land productivity. According to induced technical change theory, agricultural technological progress is not exogenously determined, but is jointly induced by factor endowment structures and market demands (Hayami and Vernon, 1985). When land factors are relatively scarce or large-scale operations are continuously advanced, technological progress will be directed towards improving land productivity. DVC accelerates the adoption of land-saving and efficiency-enhancing agricultural technologies by improving digital infrastructure and the technological application environment, allowing technological progress to better align with land resource constraints. In this process, the application of digital technologies in production enhances the precision and efficiency of land use. For example, automated machinery and autonomous operating systems improve field operation efficiency, reducing labor and resource consumption (Hu and Liu, 2025). At the same time, digital technologies accelerate the dissemination of agricultural technologies, enabling high-yield technologies and high-quality varieties to be applied more quickly in frontline production. Furthermore, the flow of information through the internet promotes rural land transfers, improving land use efficiency and the level of large-scale operations (Liu et al., 2021; He, 2016). Under the combined influence of digital technologies and the institutional environment, land factors are allocated more efficiently, thus strengthening food security.

Taken together, DVC indirectly promotes FSL through knowledge diffusion and factor reallocation effects. Accordingly, Hypothesis 2 is proposed.

> *H2*: DVC enhances FSL by improving agricultural technology training coverage and increasing land productivity.

2.3 Moderating effect of government scale in the process of DVC influencing FSL

In the process of DVC promoting FSL, government actions play a critical institutional moderating role. According to public economics and agricultural policy theory, government size is not only associated with public resource allocation capacity, but also affects the coordination efficiency between digital infrastructure and the grain production system. When the proportion of government fiscal expenditure to GDP is high, it indicates that the public sector has greater input and regulatory capacity in the agricultural and rural sectors. The government's role in resource provision, institutional protection, and policy incentives will significantly amplify the marginal effects of DVC (Wang and Hou, 2024).

Under the same level of DVC, differences in government scale will influence the actual effectiveness of DVC implementation through fiscal input capacity. From a mechanism perspective, fiscal expansion enhances the construction of rural digital infrastructure, providing the necessary resource conditions for DVC to impact FSL. Studies have shown that government agricultural expenditure is positively correlated with agricultural output and food security (Iganiga and Unemhilin, 2011; Marson, 2025). In China, agricultural fiscal expenditure mainly focuses on farmland water conservancy, agricultural technology, and infrastructure construction (Gong and Wang, 2021), which helps improve digital infrastructure such as rural internet, meteorological monitoring, and data services. The promotion of agriculture and food security through digitalization is institutionally dependent, and its effectiveness partially depends on government fiscal capacity and governance levels (World Bank, 2021). Strengthened fiscal support lowers the barriers to the application of digital technologies, accelerating the extension of agricultural informatization to the grassroots level, thereby improving the implementation efficiency of DVC in the field of grain production. Through subsidies and other fiscal support for agriculture, government departments promote the substitution of labor by agricultural machinery, increasing mechanization levels and food production efficiency (Lv et al., 2015). A larger government scale can facilitate multi-party cooperation between research institutions, digital platforms, and farmers through policy subsidies and technology promotion, deepening the integration of digitalization and grain production, thereby amplifying the effects of DVC on food production efficiency and ecological sustainability. Conversely, when government resource provision is insufficient or fiscal support is weak, digital infrastructure investment is prone to regional gaps, limiting the diffusion and application of digital technologies in rural areas, and significantly weakening the impact of DVC on FSL. Therefore, government scale plays a positive moderating role in the process of DVC influencing FSL by enhancing resource provision capacity.

> *H3*: Government scale plays a positive moderating role in the process of DVC influencing FSL (see Figure 1).

3 Research design

3.1 Data sources

This study employed provincial panel data from 31 provinces in China from 2011 to 2023 (excluding Hong Kong, Macau, and Taiwan) as the research sample. The data for the main variables are sourced as follows: rural digital inclusive finance index is taken from Peking University Digital Finance Research Center (2011–2023) agricultural patent data is sourced from the China National Knowledge Infrastructure (CNKI) patent database; agricultural technology training coverage is calculated and constructed using the method of Zhu and Ye (2024). Data for the remaining indicators are primarily obtained from the official website of the National Bureau of Statistics and the China Statistical Yearbook. Missing values for some indicators are supplemented and corrected based on the China Rural Statistical Yearbook and various provincial statistical yearbooks.

3.2 Model specification

A two-way fixed effects (TWFE) model is employed to control for unobservable individual heterogeneity and macro-level temporal shocks that may bias the estimation results. The inclusion of fixed effects helps mitigate omitted variable bias and enhances the robustness of the estimates. Continuous variables with large standard deviations are logarithmically transformed. The baseline model is specified as follows:

$$\mathrm{FS}_{i,t} = \beta_0 + \beta_1 \mathrm{DIG}_{\mathrm{i,t}} + \beta_2 \mathrm{Control}_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}$$

In the above equation, $\mathrm{FS}_{i,t}$ denotes the FSL of province i in year t, and $\mathrm{DIG}_{\mathrm{i,t}}$ represents the level of DVC, which is the core explanatory variable of this study. $\mathrm{Control}_{i,t}$ includes all control variables. μ_i denotes province fixed effects, and δ_t denotes time fixed effects, which

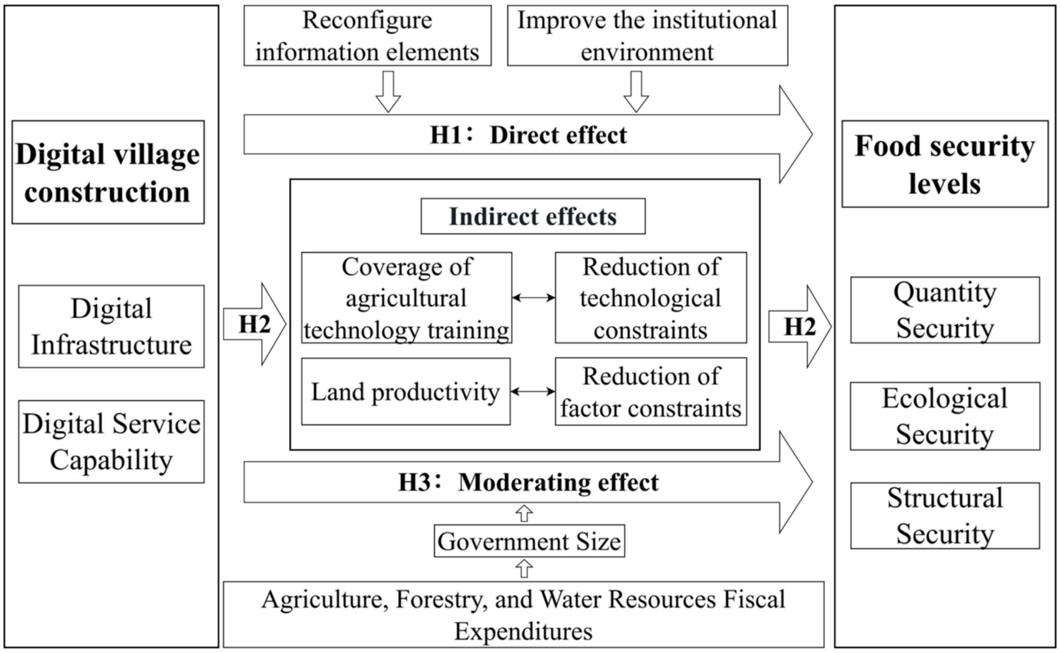

FIGURE 1
Theoretical framework diagram.

are used to control for unobserved time-invariant individual characteristics and macro-level shocks. $\varepsilon_{i,t}$ represents the random disturbance term. The estimated coefficient β_1 reflects the direction and magnitude of the direct impact of DVC on FSL.

3.3 Variable selection

3.3.1 Dependent variable

Food security is not a single concept, but rather a multidimensional one. The Food and Agriculture Organization (FAO, 2008) defines food security as having four dimensions: availability, accessibility, utilization, and stability, which encompass aspects of supply, demand, and risk. In China, the theory and policy practices related to food security focus more on ensuring grain production, emphasizing the long-term stability of food supply capacity. Based on this, this paper constructs a FSL evaluation index system that includes three dimensions—quantity security, ecological security, and structural security—within the framework of international food security theory, combined with China's practical situation, starting from the perspective of the grain production system (Cui and Dong, 2021; Yang et al., 2016; Wang et al., 2024; Xin et al., 2018).

Compared to traditional research frameworks that focus solely on output, the new era of food security evaluation places greater emphasis on the dynamic balance between yield growth, ecological constraints, and structural optimization (Zhong et al., 2024). FSL's basic guarantee lies in quantity security, while ecological security reflects sustainability requirements, and structural security represents the coordination and stability of the agricultural system (Cui and Dong, 2021). Quantity security concerns whether food supply is sufficient. In this paper, total grain production and yield per unit area are used to reflect regional food supply scale and production efficiency, which characterize quantity security. Ecological security focuses on sustainable development, and the FAO (2021) has tracked multiple sustainable development measures, including fertilizer, pesticide, and land use. This paper uses pesticide and fertilizer application intensity and soil erosion control area to measure ecological security, reflecting the sustainability of food security. Additionally, as a special commodity with public goods and strategic attributes, food security relies on a stable production structure and factor supply system (Zhong et al., 2024). This paper constructs the structural security dimension from two aspects: crop planting structure and employment structure. The crop planting structure can represent a region's ability to resist the trend of non-food crop development, while the rural employment structure concerns the stability of agricultural labor supply. Labor outflow or excessive de-agrarianization may weaken the continuity of grain production and even increase food supply risks.

In terms of indicator properties, positive indicators indicate that an increase in the variable helps improve FSL, while negative indicators suggest that an increase in the variable weakens FSL. Regarding the indicator aggregation method, this paper adopts the entropy weight method[1] to assign weights to each indicator and construct an index. The weights are determined endogenously based on the dispersion of the indicators in the sample, thus reducing subjective bias in weight assignment. This method is suitable for multi-indicator comprehensive evaluation scenarios. The final FSL evaluation index system is presented in Table 1.

1 The specific calculation steps are detailed in the Appendix.

TABLE 1 Indicator system for evaluating FSL.

Evaluation dimension	Evaluation indicator	Indicator definition	Attribute	Weight
Quantity security	Total grain output	Total grain production (10,000 tons)	+	0.352
	Grain yield per unit area	Grain yield per unit area (kg/mu or kg/ha)	+	0.072
Ecological security	Pesticide use intensity	Pesticide consumption (10,000 tons)	−	0.019
	Fertilizer use intensity	Fertilizer consumption (10,000 tons)	−	0.050
	Soil erosion control area	Area of soil erosion control (1,000 ha)	+	0.288
Structural security	Grain planting structure	Sown area of grain crops/total sown area of crops (%)	+	0.110
	Rural employment structure	Number of agricultural, forestry, animal husbandry, and fishery workers/total rural employment (%)	+	0.109

3.3.2 Independent variable

DVC is a core pathway for promoting agricultural and rural modernization. The Trendov et al. (2019) in its research on agricultural and rural digital technologies points out that the conditions for digital transformation can be divided into basic conditions and supporting conditions. Based on China's practical situation and policy support priorities, this paper constructs a DVC evaluation index system from two dimensions: digital infrastructure and digital service capacity. Following the approaches of Wan et al. (2023), Wang F. et al. (2023), and Zhu and Chen (2023), this study constructs a digital-village evaluation system from two dimensions: digital infrastructure and digital service capacity.

Digital infrastructure is the "hard support" for DVC, reflecting the level of information accessibility and the completeness of facilities. It is the prerequisite for rural digital penetration. Four indicators are used to measure it: rural internet penetration rate, rural mobile phone ownership, rural computer ownership, and the number of meteorological observation stations. The rural internet penetration rate reflects the level of network infrastructure construction, while rural mobile phone and computer ownership are quantitative indicators of digital terminal penetration, representing the basic conditions for rural digitalization. The number of agricultural meteorological observation stations is a core indicator of digital infrastructure in the agricultural sector, reflecting the level of hardware layout for agricultural digitalization. Digital service capacity, on the other hand, is the "soft guarantee" for DVC, reflecting the efficiency of digital resource allocation and the level of technology utilization in rural areas. It serves as the exogenous driving force for rural digitalization. This is measured using the digital inclusive finance index, rural residents' transportation and communication expenditure, and the number of agricultural technology patents. Digital inclusive finance index reflects the actual possibility for farmers to access credit, payments, and insurance through digital channels. The rural residents' transportation and communication expenditure quantifies the actual usage of digital communication and information services, reflecting the degree to which farmers actively access information, which can assist in optimizing food production decision-making. The level of agricultural technology is quantified by the number of agricultural technology patents, reflecting the potential for agricultural technology services and technology transfer in DVC.

There are no negative indicators in this system, as digital development is generally regarded as a promoting force. The entropy weight method is also used to determine the weights of the indicators and construct the index, ultimately forming the DVC evaluation index system, as shown in Table 2.

3.3.3 Control variables

This paper selects industrial development structure, economic development level, crop disaster situation, and agricultural mechanization level as control variables. To avoid heteroscedasticity, these variables are log-transformed in the empirical analysis to mitigate issues of right skewness and heteroscedasticity in the variable distribution, as well as to reduce the impact of extreme values. Specifically, industrial development structure is represented by the added value of the tertiary industry. The expansion of the tertiary industry may indirectly affect grain production efficiency by driving agricultural production services, or it may squeeze agricultural input due to resource "non-agriculturalization." Economic development level is represented by per capita GDP. Economically developed regions usually have greater capacity to invest in agricultural infrastructure construction, agricultural technology research and development, and may also focus more on ecological protection to safeguard food ecological security. Its development level directly or indirectly impacts FSL. Crop disaster situation is represented by the affected area. The affected area is associated with the natural risk impact on food production. An increase in the affected area will lead to reduced grain production and damage to arable land ecology. Agricultural mechanization level is a key indicator of traditional agricultural modernization. Its improvement can increase grain production efficiency and stabilize yield. This paper uses total agricultural mechanization power to represent the level of agricultural mechanization.

TABLE 2 Evaluation indicator system for DVC.

Evaluation dimension	Evaluation indicator	Indicator definition	Attribute	Weight
Digital infrastructure	Rural internet penetration rate	Rural internet penetration rate (%)	+	0.235
	Rural mobile phone ownership	Average number of mobile phones owned per 100 rural households (units)	+	0.078
	Rural computer ownership	Average number of computers owned per 100 rural households (units)	+	0.087
	Number of meteorological observation stations	Number of agricultural meteorological service stations (units)	+	0.108
Digital service capability	Digital inclusive finance index	Digital inclusive finance index	+	0.089
	Transportation and communication expenditure	Per capita transportation and communication expenditure of rural residents (CNY)	+	0.106
	Agricultural science and technology level	Number of agricultural science and technology patents (items)	+	0.298

3.3.4 Mechanism variables

Based on the theoretical analysis above, DVC may indirectly promote FSL through two pathways: increasing agricultural technology training coverage and improving land productivity. The former reflects the diffusion of knowledge and skills in food production, indicating the farmers' mastery of production techniques and field management capabilities. The latter reflects the efficiency of resource allocation in food production under digital empowerment, indicating the comprehensive allocation effectiveness of land, labor, and technology. Following the method of Zhu and Ye (2024), the coverage of agricultural technical training is measured by the ratio of graduates from rural adult culture and technical training schools to the number of rural employed persons. According to the approach of Wang et al. (2024), land productivity is measured as the ratio of total agricultural output value to cultivated land area (see Table 3).

3.4 Descriptive statistics of features

Figure 2 displays the spatial distribution pattern of DVC and FSL levels across Chinese provinces. Overall, the level of DVC shows a spatial pattern of decreasing from east to west. Coastal provinces in the eastern region generally have higher levels, with an average index of 0.334, reflecting well-developed digital infrastructure and strong technological penetration. Most provinces in the central region are at a moderate level, with an index of 0.296, indicating relatively balanced digital development. The western and southwestern regions have significantly lower indices, with an index of 0.249. Some provinces are still in the early stages of DVC, and regional digital development is highly unbalanced.

The level of FSL shows a spatial pattern of "higher in major production areas, lower in non-major production areas," with the average index in major production areas at 0.459, higher than the 0.241 in non-major production areas. The three northeastern provinces, the central grain production areas, and the Huang-Huai-Hai Plain generally fall into higher gradients, forming the core stable areas of China's food security, while some southeastern coastal areas have relatively low FSL due to land resource constraints and a high degree of non-food crop development. Some western provinces are constrained by natural conditions, inadequate infrastructure, and limited technical support, resulting in generally weaker FSL.

From a spatial comparison, the distribution of DVC and FSL is not fully aligned. The eastern region has high levels of digitalization, but its FSL is not outstanding, while the central major production areas, despite having moderate levels of digitalization, show significantly higher FSL. The western region falls into lower gradients for both indicators. This discrepancy suggests that there may be regional dependencies and structural differences between DVC and FSL, providing important spatial context for the subsequent analysis.

4 Empirical results and analysis

4.1 Baseline regression results

Table 4 reports the estimated results of the impact of DVC on FSL. Columns (1) to (3) present the estimated results using ordinary standard errors, robust standard errors, and standard errors obtained through 1,000 bootstrap random sampling, respectively. The results show that, regardless of the standard error method used, the estimated coefficient of DVC is positive and significant at the 1% level, indicating that DVC has a significant positive impact on FSL. Specifically, holding other conditions constant, for every 1-unit increase in DVC, the FSL index increases by 0.083 units. This result suggests that the enhancement of rural digital infrastructure and digital service capacity can significantly improve the quantity, structure, and ecological security of food production by optimizing information transmission and resource allocation efficiency, thereby enhancing overall FSL. Hypothesis H1 is supported.

TABLE 3 Variable definitions and descriptive statistics.

Variable	Definition	Mean	Std. Dev.
FSL	Calculated based on the food security evaluation indicator system	0.3324	0.1411
DVC	Calculated based on the DVC evaluation indicator system	0.2938	0.1302
Agricultural technology training coverage	Number of graduates from rural adult cultural and technical training schools/number of rural employed persons (%)	0.0848	0.1031
Land productivity	Gross agricultural output value/cultivated land area (billion CNY/million mu)	0.0006	0.0004
Industrial development structure	Value added of the tertiary sector (billion CNY)	9.1086	1.0353
Economic development level	Gross regional product / annual permanent population (billion CNY/million persons)	1.6791	0.4716
Crop disaster situation	Affected crop area (1,000 ha)	5.6634	1.7157
Agricultural mechanization level	Total power of agricultural machinery (10,000 kW)	7.6505	1.1380

4.2 Robustness analysis

Trimming extreme values: Considering that the composite indices of DVC and FSL, calculated using the entropy weight method, may be influenced by outliers, and that some provinces or years exhibit large distributional differences, this study applies a 5% winsorization at both ends to reduce the impact of extreme values. The results in column (1) of Table 5 show that, after trimming the outliers, the regression coefficient for DVC remains significantly positive at the 1% level, confirming the robustness of the baseline regression results.

Lagging variables by one period: Given that the effects of DVC on FSL may exhibit temporal lags, this study lags the DVC variable by one period and re-estimates the model. The results in column (2) of Table 5 show that the lagged coefficient remains significantly positive, consistent with the baseline regression. This suggests that the promoting effect of DVC on FSL is not only immediate but also persistent and cumulative over time.

Excluding the impact of the COVID-19 pandemic: The exogenous shocks induced by the COVID-19 pandemic may have substantially affected both FSL and DVC. To address this concern, observations from 2020 onward are excluded, and the model is re-estimated. The results in column (3) of Table 5 show that the coefficient of DVC remains positive and significant at the 1% level, with only minor changes in magnitude. This indicates that the findings are not driven by short-term pandemic-induced fluctuations and that the positive effect of DVC on FSL remains robust across different economic and social environments.

4.3 Endogeneity concerns

In the identification of the impact of DVC on FSL, potential endogeneity issues arise. On one hand, reverse causality may lead to endogeneity bias, as regions with higher FSL tend to have better agricultural infrastructure, stronger policy support, and are more likely to promote DVC. On the other hand, omitted variable bias cannot be ignored, as factors such as institutional environment, local governance capacity, and policy implementation strength affect both DVC and FSL, potentially leading to biased OLS estimates. To address this, this paper employs the Two-Stage Least Squares (2SLS) method for robustness checks. Following the methods of Zhao et al. (2020), He and Zhang (2022) and Zhang et al. (2019), this paper selects the number of post and telecommunication bureaus in each province in 1984 and the distance between each city and Hangzhou as instrumental variables. Since the 1984 postal density and geographic distance are cross-sectional data, the paper constructs interaction terms between the national average DVC index and the number of post offices and geographic distance to generate panel instrumental variables.

Regarding the number of post and telecommunication bureaus in each province in 1984, on one hand, the telecommunication infrastructure in the 1980s was a crucial reflection of regional information dissemination and communication conditions. The internet is an extension and development of traditional communication technologies, and the historical telecommunication infrastructure in the region influenced the subsequent application of internet technology through factors such as technological level and usage habits (Zhao et al., 2020). Empirical evidence also shows that DVC is strongly correlated with the existing level of telecommunication infrastructure, satisfying the relevance requirement for the instrumental variable. On the other hand, traditional communication media, represented by post and telecommunication bureaus, are used less frequently today, and their influence on the socio-economic environment has gradually diminished (Lin and Zhu, 2022), with no direct causal link to the current FSL, thus meeting the exclusion restriction for the instrumental variable.

Regarding geographic distance, on one hand, DVC is influenced by the radiation effect of core digital hubs. Hangzhou, as a digital economy hub, has a technological diffusion effect that diminishes with increasing geographic distance. The distance from provincial capitals to Hangzhou is related to the ease of digital technology diffusion to rural areas. Areas closer to Hangzhou generally have higher DVC advancement efficiency, thus meeting the relevance requirement for the instrumental variable. On the other hand, the distance from provincial capitals to Hangzhou is a historically established geographic endowment, which does not directly interfere with core aspects such as crop cultivation and production efficiency but only indirectly affects DVC through the diffusion of digital technology. Therefore, both variables satisfy the relevance and exogeneity assumptions for instrumental variables.

The regression results in column (1) of Table 6 show that the instrumental variables are statistically significant, and their direction of effect is consistent with theoretical expectations, satisfying the relevance

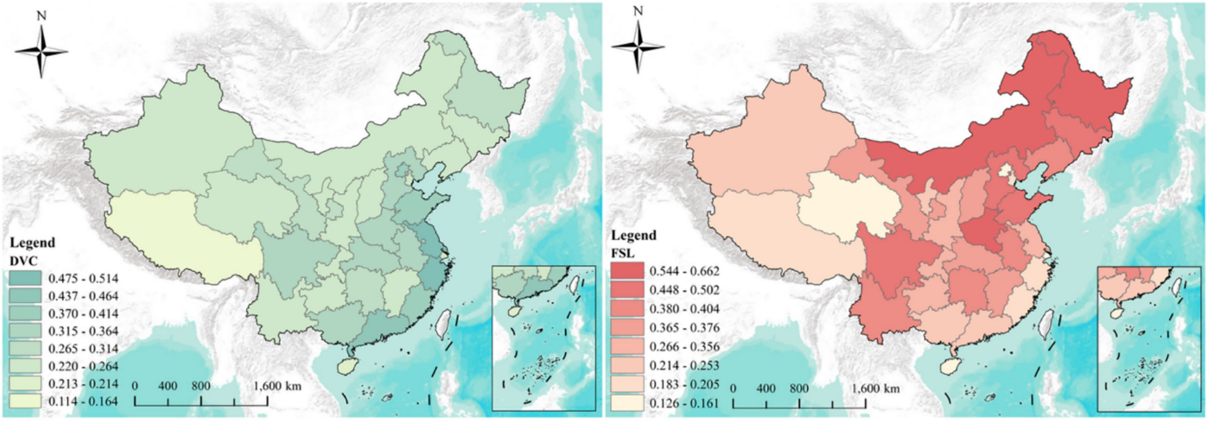

FIGURE 2
Spatial distribution of DVC and FSL. The map file is sourced from the National Platform for Common Geo Spatial Information Services, map review number GS (2024)0650, the base map has not been modified.

TABLE 4 Baseline regression results.

Variables	(1)	(2)	(3)
	Conventional std. errors	Robust std. errors	Bootstrap (1,000 replications)
DVC	0.083*** (2.65)	0.083*** (2.68)	0.083*** (2.60)
Agricultural mechanization level	0.022*** (3.34)	0.022** (2.44)	0.022** (2.33)
Economic development level	0.058*** (2.66)	0.058* (1.89)	0.058* (1.80)
Crop disaster situation	0.001 (0.87)	0.001 (0.82)	0.001 (0.80)
Industrial development structure	−0.080*** (−3.97)	−0.080*** (−2.94)	−0.080*** (−2.83)
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	0.766*** (4.67)	0.766*** (3.64)	0.766*** (3.45)
Observations	403	403	403
R-squared	0.987	0.987	0.978

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$; Numbers in parentheses denote t-statistics.

TABLE 5 Robustness analysis results.

Variables	(1)	(2)	(3)
	Excluding outliers	Lagged independent variable	Excluding COVID-19 period
DVC	0.0829*** (0.0289)	0.0664** (0.0306)	0.0798*** (0.030)
Constant	0.0863 (0.0895)	0.841*** (0.215)	0.286*** (0.014)
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	403	372	279
R-squared	0.990	0.989	0.989

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$; Robust standard errors in parentheses.

TABLE 6 Endogeneity test.

Variables	First stage	Second stage
	(1)	(2)
DVC		0.223*** (0.066)
IV_Post	0.0006*** (0.000)	
IV_DistHZ	−0.0002*** (0.000)	
Controls	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
p-value	0.010	
F statistic	31.96	
Overidentification test *p*-value	0.073	

*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. IV_Post denotes the number of postal bureaus in 1984; IV_DistHZ denotes the geographic distance to Hangzhou.

condition. The second-stage regression results show that the estimated coefficient for DVC is 0.223, which is significantly positive at the 1% level, indicating that, after considering potential endogeneity bias, the instrumental variable estimates align with the direction of the baseline regression, providing supplementary evidence for the impact of DVC on FSL. Furthermore, the Durbin–Wu–Hausman (DWH) test yields a *p*-value of 0.010, rejecting the exogeneity hypothesis at the 1% level, suggesting that DVC is an endogenous variable. The Cragg-Donald Wald F-statistic is 31.96, which is greater than the standard critical value of 10, indicating no weak instrument problem. The *p*-value of the overidentification test is 0.0733, and the null hypothesis of instrument exogeneity is not rejected at the 5% level. However, given that the *p*-value is close to the significance level, caution should be maintained, and the exogeneity of the instrument is considered to be robust.

5 Further analysis

5.1 Mechanism testing

Building on the previous theoretical analysis, this paper further examines the causal mechanisms through two mediating pathways: agricultural technology training coverage and land productivity, to explore how DVC impacts FSL. The mechanism analysis follows the mediation effect approach commonly used in economics, as proposed by Jiang (2022). This approach primarily tests the causal relationship between the core explanatory variable and the mediating variables, while ensuring the theoretical directness of the effect of the mediating variable on the dependent variable, without relying on the coefficient decomposition of traditional stepwise methods, thus avoiding bias from the endogeneity of the mediating variable. Therefore, the mechanism analysis in this paper aims to provide empirical evidence at the pathway level, rather than precisely decomposing the size of the mediation effect. The regression results are presented in Table 7.

TABLE 7 Analysis of mechanism impact regression results.

Variables	(1)	(2)	(3)	(4)
	Technical training coverage	Land productivity	FSL	FSL
DVC	0.237*** (4.76)	0.001*** (2.86)	0.090*** (0.031)	0.086*** (0.031)
Constant	0.286 (1.07)	−0.007*** (−4.23)	0.775*** (0.211)	0.728*** (0.209)
Observations	403	403	403	403
Adjusted *R*-squared	0.930	0.877	0.987	0.987
Control variables	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$; Robust standard errors in parentheses.

The regression results in column (1) of Table 7 show that the coefficient for the impact of DVC on agricultural technology training coverage is 0.237, which is statistically significant at the 1% level. This indicates that for every 1-unit increase in DVC, agricultural technology training coverage increases by approximately 0.24 units. This suggests that DVC has a significant practical impact on improving the coverage of agricultural technology training, thereby providing human and technical support for FSL. Rural digitalization enables governments and research institutions to more efficiently disseminate agricultural information and technical knowledge, providing farmers with timely training resources and decision-making guidance. Previous studies have pointed out that one of the main reasons for excessive pesticide and fertilizer use is the lack of technical information and guidance. However, farmers who have received systematic training can effectively reduce fertilizer usage and improve field management (Jia et al., 2013; Ying and Zhu, 2015). The acceptance of new knowledge and technologies by farmers helps to increase crop yields (Hua et al., 2013). Therefore, expanding agricultural technology training coverage helps enhance the sustainability of the food security system from both production efficiency and ecological security perspectives, and DVC provides effective conditions for this.

The regression results in column (2) of Table 7 show that DVC significantly increases land productivity at the 1% level. This result suggests that DVC may enhance production efficiency through improved information precision and optimized factor allocation. Increasing the efficiency of cultivated land use is widely regarded as a key strategy for ensuring China's food security (Liu et al., 2008). Under the context of DVC, the improvement of information and communication infrastructure and digital service capacity helps enhance the precision of market information supply and production management, thereby improving the efficiency of labor and land factor allocation (Ogutu et al., 2014). Furthermore, the improvement in digital conditions provides the foundation for production entities to more effectively access land use information, production environment data, and technical services, allowing them to better optimize production structures and increase land productivity (Chandio et al., 2024; Peng and Huang, 2024) Thus, the increase in land productivity supports FSL.

To enhance the credibility of the conclusions, this paper further incorporates the mediating variables into the regression model. The results, shown in columns (3) and (4) of Table 7, indicate that after controlling for agricultural technology training coverage and land productivity, the impact of DVC on FSL remains statistically significant and positive, with the direction and significance remaining stable. These results provide supportive empirical evidence that DVC influences FSL through the enhancement of agricultural technology training coverage and land productivity, thereby partially supporting Hypothesis H2.

5.2 Spatial effect analysis

Based on the global Moran's I test results, FSL exhibited significant positive spatial autocorrelation between 2012 and 2023, with the Moran's I values passing the test at the 1% significance level. The spatial autocorrelation of DVC was not significant in the earlier period of the sample but gradually became significantly positive starting from 2016, passing the test at the 10% significance level and above. This indicates that the spatial agglomeration characteristics of DVC began to emerge in the later period of the sample. The results show that both variables exhibit varying degrees of spatial dependence (see Tables 8, 9).

Building on the significant spatial correlation of FSL, this paper applies the testing framework proposed by Elhorst (2014), using LM tests, Hausman tests, SDM simplification tests, and fixed effects structure tests. The Hausman test results reject the random effects model at the 5% significance level. Both the Wald test and LR test reject the null hypothesis of the spatial Durbin model (SDM) being degenerate to the spatial lag model (SAR) and the spatial error model (SEM) at the 1% significance level, confirming the appropriateness of using the SDM model. Regarding the fixed effects structure, the LR test further rejects models that control only for time effects or individual effects, thus confirming the use of the two-way fixed effects SDM.

The results in column (3) of Table 10 show a significant positive relationship between DVC and local FSL, with the regression coefficient being positive at the 1% significance level, indicating that improvements in digital infrastructure and digital service capacity promote local FSL. The spatial lag term for DVC is significantly negative, suggesting that digital progress in neighboring areas does not drive local FSL improvements. In fact, it may generate a certain crowding-out effect through mechanisms such as factor mobility, resource competition, or regional development imbalance, thereby weakening the positive spatial spillover effect between regions. The spatial autoregressive coefficient (ρ) in the two-way fixed effects model does not pass the significance test, indicating that after incorporating the explanatory variables and their spatial lag terms, the spatial linkage effect of FSL itself is not significant. Further decomposition of effects reveals that the direct effect of DVC on FSL is significantly positive, mainly promoting local FSL through improved digital infrastructure and service capacity. However, the indirect effect is significantly negative, indicating that the digital improvement between regions has certain limitations, showing a negative impact of spatial lag effects on cross-regional spillovers, leading to the total effect not passing the significance test.

TABLE 8 Moran's I index statistics for DVC and FSL.

Year	DVC		FSL	
	Moran's I	Z-value	Moran's I	Z-value
2012	−0.020	0.117	0.393***	3.555
2013	0.008	0.356	0.398***	3.605
2014	0.056	0.766	0.372***	3.398
2015	0.127	1.374	0.358***	3.292
2016	0.159*	1.649	0.371***	3.394
2017	0.186*	1.887	0.391***	3.548
2018	0.167*	1.717	0.383***	3.479
2019	0.180*	1.806	0.356***	3.268
2020	0.170*	1.743	0.365***	3.336
2021	0.190*	1.910	0.358***	3.278
2022	0.194*	1.952	0.364***	3.338
2023	0.208**	2.061	0.361***	3.313

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$; Due to limitations in the spatial weight matrix and sample connectivity, the global Moran's I for 2011 could not be computed.

TABLE 9 Re-examination of spatial autocorrelation based on geographic adjacency matrix.

Test type	Observations	Statistic	p-value
Spatial error			
Moran's I	403	8.282	0.000
LM	403	64.174	0.000
Robust LM	403	0.074	0.785
Spatial lag			
LM	403	114.709	0.000
Robust LM	403	50.610	0.000

The null hypothesis of the LM test is that there is no spatial dependence in the model residuals, conditional on the specified spatial weight matrix.

TABLE 10 Spatial econometric model estimation results.

Variables	(1)	(2)	(3)
	Time fixed effects	Individual fixed effects	Two-way fixed effects
DVC	−0.4220*** (0.0626)	0.1047*** (0.0297)	0.1313*** (0.0304)
W × DVC	0.1589 (0.1117)	−0.0856** (0.0424)	−0.0984** (0.0480)
ρ	0.3055*** (0.0642)	0.1561** (0.0642)	−0.0665 (0.0780)
Direct effect	−0.4166*** (0.0668)	0.1033*** (0.0305)	0.1340*** (0.0313)
Indirect effect	0.0517 (0.1482)	−0.0771 (0.0475)	−0.0999** (0.0455)
Total effect	−0.3650** (0.1823)	0.0262 (0.0567)	0.0341 (0.0535)
Observations	403	403	403
R-squared	0.7674	0.0213	0.0269
Time fixed effects	Yes	No	Yes
Individual fixed effects	No	Yes	Yes

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

5.3 Heterogeneity analysis

Building on the regional correlation evidence provided by the spatial model, this paper further examines the differentiated effects of DVC from the perspectives of location and functional positioning.

5.3.1 Heterogeneity across major and non-major grain-producing regions

There are significant differences between major and non-major grain producing areas in terms of production models, resource

TABLE 11 Heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)	(5)
	Major grain-producing areas	Non–major grain-producing areas	Eastern region	Central region	Western region
DVC	0.105*** (6.30)	−0.003 (−0.09)	0.078*** (2.93)	0.114*** (5.72)	0.088*** (3.47)
Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	403	403	403	403	403
R-squared	0.987	0.987	0.986	0.986	0.986

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$; Robust standard errors in parentheses.

endowments, and policy support. Based on this, this paper divides the 31 provinces into two groups: major grain producing areas and non-major grain producing areas, to examine the regional heterogeneity of DVC's impact on FSL. The regression results in columns (1) and (2) of Table 11 show that DVC has a significantly positive effect on FSL in major grain producing areas at the 1% significance level. In these areas, for every 1-unit increase in DVC, FSL increases by 0.105 units, demonstrating a strong positive marginal effect. In contrast, in non-major grain producing areas, DVC is not statistically significant. This indicates that the positive enabling effect of DVC on FSL is primarily concentrated in major grain producing areas. This difference arises from the structural bias in policy and resource allocation. Since 2003, when the government explicitly defined major grain producing areas, fiscal and technological policies have consistently favored these regions (Cui and Dong, 2021). Major grain producing areas, with a focus on food security, have concentrated digital resources in grain cultivation, with large contiguous areas of farmland and high levels of scale in production, making it easier for DVC to be implemented and scaled, thereby significantly improving production efficiency and risk response capabilities. In contrast, non-major grain producing areas have more diversified economic structures, with digital resources often directed toward rural tourism, specialty agriculture, or urban–rural integration industries, leading to insufficient digital investment in the grain production process. Therefore, the promoting effect of DVC on FSL is more significant in major grain producing areas, while in non-major grain producing areas, it is constrained by the dispersion of resources and the dilution of effects.

5.3.2 Regional heterogeneity

Based on natural geographic location and economic development characteristics, this paper further divides the national sample into three regions: East, Central, and West. The regression results in columns (3) to (5) of Table 11 show that the estimated coefficients for DVC on FSL in the East, Central, and West regions are all significantly positive at the 1% significance level, but exhibit distinct regional gradient characteristics. The coefficient for the Central region is the largest, followed by the West and East regions, indicating that DVC has a stronger enabling effect on the FSL in the central and western major grain producing areas. The marginal effect of digital empowerment is closely related to regional agricultural structure, factor endowments, and policy environment. The Central region, as the core grain producing belt, benefits from well-established large-scale grain production and deep integration with digitalization. Through DVC, it empowers key processes such as precision management of farmland and accurate allocation of agricultural inputs, leading to an improvement in FSL. In recent years, the West has accelerated the construction of digital infrastructure with policy support, effectively addressing information asymmetry in traditional grain production. This has filled gaps in the flow of agricultural production factors, significantly improving the efficiency of grain resource utilization and the coordination of various production stages. Although the East has the most developed digital infrastructure, its impact on FSL is the weakest. This is primarily because the agricultural share in the East is relatively low, and digitalization is more focused on extending industrial chains and high-value-added sectors, leading to a more limited effect on FSL. For instance, digital resources are more directed toward high-value economic crops, leaving staple grain production with insufficient digital support, or non-agricultural industries raise land and labor opportunity costs, which suppresses investment in staple crop production.

5.3.3 Distributional effects across FSL

Considering the differences in digital absorption capacity across regions with varying levels of FSL, this paper further employs quantile regression to examine the distributional effect of DVC on FSL, with the results shown in Table 12. The results indicate that the effect of DVC exhibits significant threshold characteristics. At the 0.25 quantile, where FSL is relatively low, the coefficient of DVC is 0.0103 and not statistically significant, indicating that the enabling effect does not materialize. At the median level (0.5 quantile), the coefficient is 0.0759, significant at the 5% level, demonstrating a stable positive marginal effect. At the 0.75 quantile, which represents the mid-high level of FSL, and the 0.9 quantile, representing high FSL, the coefficient is significantly positive at the 1% level, with the highest coefficient observed at the highest level, indicating the strongest enabling effect. In summary, the positive impact of DVC on FSL gradually becomes more pronounced once the threshold is surpassed, and the effect strength increases as FSL improves.

Effective digital empowerment relies on the resource endowments associated with food production, particularly elements such as land resources and agricultural labor. Regions with low FSL typically lack adequate production infrastructure and conditions. This may be due to a lack of resource endowments such as land, or insufficient labor and agricultural machinery, which constrain food production. As a result, production factors are unable to support the effective

TABLE 12 Distributional effects of FSL.

Variables	(1)	(2)	(3)	(4)
	25%	50%	75%	90%
DVC	0.0103 (0.0263)	0.0759** (0.0380)	0.0645*** (0.0237)	0.0825*** (0.0258)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	0.442*** (0.134)	0.606*** (0.190)	0.478*** (0.169)	0.451 (0.947)
Observations	403	403	403	403

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$; Robust standard errors in parentheses.

integration and scaling of digital technology. While digitalization may not significantly improve FSL in the short term, this does not imply that DVC is ineffective in low FSL areas. Rather, its effectiveness is more dependent on the gradual improvement of foundational conditions. In regions with medium to high FSL, where conditions for land, factor allocation, and the organization of agricultural production are more established, digital technology is more likely to complement the existing production systems and create amplifying effects, thereby demonstrating a stronger marginal impact. Therefore, the effect of DVC on FSL shows significant stage-dependent differences, with a reinforcing effect in areas with medium to high FSL and a damping effect in areas with low FSL.

5.4 Moderating effect

The process of DVC empowering FSL requires corresponding policy and fiscal support, with local fiscal expenditure on agricultural, forestry, and water affairs serving as a key indicator of government size in the agricultural sector. Government size not only affects the fiscal capacity to support digital infrastructure construction and technology promotion but also influences the depth of digital technology penetration and implementation effectiveness within the agricultural system. To identify the moderating role of government size in the process of DVC impacting FSL, this paper constructs an interaction term between DVC and government size for regression analysis.

The regression results in Table 13 show that the coefficient of the interaction term is 0.0849, and it is statistically significant at the 1% level, meaning that, ceteris paribus, for every 1-unit increase in government size, the marginal empowering effect of DVC on FSL increases by an additional 0.0849 units. This indicates that government size plays a significant positive moderating role, with larger government size leading to stronger fiscal and policy support, effectively lowering the implementation threshold for DVC and amplifying its positive empowering effect on FSL. Specifically, at the hardware level, larger government size corresponds to stronger fiscal mobilization and resource allocation capabilities, which can mobilize more funds to core areas of DVC, accelerating the deployment and upgrading of digital infrastructure, such as Internet of Things (IoT) monitoring devices, smart irrigation systems, and big data platforms for food production. This promotes the deep integration of digital facilities with the entire food production process and alleviates the barriers to the rural implementation of digital technologies. At the

TABLE 13 Moderation effect test.

Variables	FSL
Government size × DVC	0.0849*** (0.0242)
Controls	Yes
Province FE	Yes
Year FE	Yes
Constant	0.957*** (0.224)
Observations	403
R-squared	0.988

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$; Robust standard errors in parentheses.

software level, sufficient fiscal expenditure ensures the provision of public services for food production, supporting targeted digital technology training to improve farmers' digital skills and technological absorption capabilities. Furthermore, relying on fiscal subsidies and policy guidance, it enhances complementary services such as digital finance, lowering the adoption threshold and risks for farmers. Overall, the larger the local government size, the stronger its fiscal and resource coordination capacity, which helps bridge the gap between digital technology and food production, thereby amplifying the positive empowering effect of DVC. Hypothesis H3 is supported.

6 Discussion

This study explores the impact of DVC on FSL. The empirical results show a significant positive correlation between the two, indicating that DVC can influence FSL through various channels. Specifically, DVC positively impacts FSL by improving both digital infrastructure and service capabilities. This result is consistent with existing research and further validates the crucial role of DVC in enhancing food security within the agricultural production process. While most existing studies on DVC employ the DID method to assess the effects of policies (Wang P. et al., 2023; Gao et al., 2025), this study differentiates itself by clarifying that DVC is not solely reliant on the widespread adoption of technology, but rather on the synergistic effect of digital infrastructure and service capabilities.

This study further investigates the mechanisms through which DVC influences FSL, finding that DVC has a positive impact on FSL by improving agricultural technology training coverage and enhancing land productivity. The role of agricultural technology training coverage lies in increasing farmers' knowledge and adoption of technology (Hussain et al., 1994), and it also represents a transformation in the diffusion model of agricultural knowledge through digital technologies. The mediating effect of land productivity provides new empirical support for the application of the induced technological change theory in the digital era. In the future, improvements in food productivity will rely more on technological adaptation rather than increased resource inputs (Cui and Shoemaker, 2018). The findings also indicate that the positive impact of DVC on FSL is the result of a synergistic combination of multiple factors, rather than the penetration of technology alone. This suggests that efforts should focus on increasing investment in digital infrastructure, enhancing digital services, promoting agricultural technology training, and improving land use efficiency to drive DVC and, in turn, safeguard FSL.

Although DVC is theoretically expected to exert a generally positive effect, the empirical results indicate that its impact on FSL does not automatically diffuse across all regions. In practice, the effectiveness of DVC is highly contingent on the degree to which local production systems are deeply integrated with digital elements. This finding runs counter to existing evidence suggesting that digital rural development generates spatial spillover effects in economic and environmental domains (Liu et al., 2022; Hu et al., 2025; Shan and Shi, 2025). It implies that digital investment alone is insufficient to ensure a comprehensive improvement in FSL; instead, the magnitude of digitalization's effects is shaped by regional characteristics, industrial foundations, and differences in resource endowments. Accordingly, policy design should place greater emphasis on local conditions and adopt differentiated DVC strategies tailored to regional contexts, thereby enhancing their potential to promote FSL.

The results of the heterogeneity analysis reflect the contextual adaptability of digital rural construction in enhancing FSL, providing crucial insights for policy implementation. Specifically, the positive effect of DVC on FSL is significantly stronger in grain-producing regions compared to non-producing regions. This is primarily due to the functional orientation of these regions centered on grain production, where their large-scale and intensive production characteristics are highly compatible with the application of digital technologies. This conclusion is consistent with existing studies (Zhu et al., 2025). The regional heterogeneity results indicate that the impact of DVC on FSL is more pronounced in the central and western regions, while in the eastern regions, the expected stronger effect of digital transformation does not materialize. Despite higher levels of DVC in the eastern regions, its effect on FSL is weaker, largely due to constraints related to agricultural resource endowments and the encroachment of non-agricultural development, which hinder the full utilization of digital investments in improving FSL. The quantile regression results further demonstrate the threshold effect of DVC, with its positive impact on FSL being more significant in areas with higher baseline food security. This suggests that the effectiveness of DVC is contingent upon certain foundational conditions. This finding provides evidence for differentiated policy approaches in different regions.

The study also delves into the moderating role of government size in the relationship between DVC and FSL. Government plays a crucial role in the rapid reallocation of resources and the development of digital rural life. Rural digitization implies the reorientation of resource elements toward rural areas (Xiong et al., 2024). In particular, under conditions of substantial fiscal investment, governments can support the role of DVC in enhancing FSL by optimizing policy design and strengthening resource provision. Therefore, the government's role extends beyond investment in digital technologies alone and should place greater emphasis on optimizing fiscal expenditure, promoting policy coordination, and fostering technological innovation. This provides important theoretical support for policy formulation.

7 Conclusions and policy implications

This study systematically evaluates the impact of DVC on FSL and its underlying mechanisms using panel data from 31 Chinese provinces between 2011 and 2023. The results show that DVC significantly promotes the improvement of FSL. Mechanism analysis indicates that DVC enhances FSL through two pathways: increasing agricultural technology training coverage and improving land productivity. On one hand, DVC strengthens agricultural technology training, enhancing farmers' ability to absorb production technologies, improving agricultural decision-making environments and resource allocation, thus providing support for FSL from both human and technological perspectives. On the other hand, by precisely matching production factors and environmental information through digitalization, DVC improves land productivity and production intensification, thereby comprehensively enhancing FSL. Spatial panel analysis results show that the impact of DVC on FSL is primarily achieved by strengthening internal production capacity within regions, rather than relying on cross-regional diffusion mechanisms.

Further analysis reveals significant regional differentiation and policy dependence in the effects of DVC on FSL. At the production-zone level, DVC has a significantly positive effect on major grain-producing areas, while its impact in non-major grain-producing areas is insignificant. At the regional level, a positive effect is observed in the eastern, central, and western regions, with the strongest effect in the central region, followed by the western region, and the weakest effect in the eastern region. Quantile regression results show that the promoting effect is more pronounced in areas with higher FSL, exhibiting a pattern of strengthening at higher levels and attenuation at lower levels. Additionally, government size plays a significant positive moderating role in the relationship between DVC and FSL.

Based on the above findings, this study proposes the following policy recommendations:

First, establish a regionally differentiated promotion mechanism for DVC. Based on the empirical characteristics showing stronger effects in major grain-producing areas and more significant empowerment in the central and western regions, prioritize the demonstration and implementation of DVC in the central and western regions and major grain-producing areas. Enhance rural digital infrastructure and digital public services, and consider incorporating the effectiveness of DVC in the food production sector into the local agricultural governance performance evaluation system, providing institutional and environmental support for digital applications. In the eastern and non-major grain-producing areas, set minimum investment requirements for food-related public services in DVC to prevent excessive concentration of digital resources in non-agricultural sectors. In regions with lower FSL, prioritize ensuring the accessibility of digital infrastructure and services, set quantified targets for digital infrastructure coverage, and institutionalize the downward diffusion of digital resources.

Second, strengthen rural digital literacy training and digital service capability in agriculture. Fully utilize the role of agricultural technology training, leveraging DVC to integrate agricultural technology promotion, vocational education, and public service resources, and build a blended online and offline digital skills training system. Focus on food production needs, guide farmers to improve their production skills and information comprehension abilities, and enhance their access to and application of agricultural technologies, market information, and risk warnings. Use digital platforms to dynamically match training content with farmers' needs, improving the support efficiency of digital services for food production.

Third, improve the multi-level DVC platform and data coordination mechanism. In regions with higher FSL, establish a regional-level digital resource scheduling platform to integrate data resources related to agriculture, meteorology, land, and food production public services through the platform, enhancing the digital level of food security governance and risk prevention. In regions with lower FSL, reduce the barriers to digital application through regional cooperation and platform sharing, improving the collaborative efficiency of food production and public services. Meanwhile, improve the data feedback and governance response mechanism to strengthen the dynamic adjustment capacity of the DVC system in addressing agricultural risks and resource allocation issues.

Fourth, strengthen government fiscal support and DVC performance-oriented mechanisms. Position DVC as an essential public investment for ensuring FSL, increasing fiscal support for rural digital infrastructure and relevant application scenarios. Include key components, such as smart agricultural machinery and IoT sensing devices, in the priority subsidy scope, particularly in the central and western regions and major grain-producing areas, to increase investment intensity. Establish a dedicated assessment mechanism, clarifying the minimum allocation of fiscal funds for agricultural technology training and land quality improvement, and use fiscal incentives to promote the synergistic effect of DVC and FSL.

This study has several limitations. First, due to data availability constraints, this study uses provincial-level panel data for analysis, which limits the ability to capture heterogeneity at the county or household level. This, to some extent, restricts the applicability of the conclusions at the micro level. Second, while the potential endogeneity issue is addressed using the instrumental variable approach and various robustness tests, the endogeneity effect may not be fully eliminated due to model specification and measurement errors. Therefore, the analysis of the mechanisms is primarily based on the statistical associations and supporting evidence provided by the regression results, and the explanations of the mechanisms should be considered as empirical inferences. Future research can further verify the related mechanisms by using more granular data or structural models. Third, this study does not attempt to construct or propose a new food security theoretical framework but empirically tests the role of DVC in the Chinese institutional context based on existing digital economy and agricultural production theories. Due to the limitations of the research design, the theoretical contribution of this study is more reflected in the supplement and contextual expansion of empirical evidence, rather than a reconstruction of the food security theory itself.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.cnki.net/.

Author contributions

ML: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. SH: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. HC: Writing – review & editing, Formal analysis, Methodology. XZ: Writing – review & editing, Funding acquisition, Project administration, Supervision.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Aker, J. C. (2011). Dial “a” for agriculture: a review of information and communication technologies for agricultural extension in developing countries. *Agric. Econ.* 42, 631–647. doi: 10.1111/j.1574-0862.2011.00545.x

Aker, J. C., Ghosh, I., and Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agric. Econ.* 47, 35–48. doi: 10.1111/agec.12301

Campbell, B. M., Vermeulen, S. J., Aggarwal, P. K., Corner-Dolloff, C., Girvetz, E., Loboguerrero, A. M., et al. (2016). Reducing risks to food security from climate change. *Glob. Food Secur.* 11, 34–43. doi: 10.1016/j.gfs.2016.06.002

Chandio, A. A., Ozdemir, D., Gokmenoglu, K. K., Usman, M., and Jiang, Y. (2024). Digital agriculture for sustainable development in China: the promise of computerization. *Technol. Soc.* 76:102479. doi: 10.1016/j.techsoc.2024.102479

Chen, H., Liu, M., Xie, S., and Chen, L. (2025). A study on the impact of rural industrial integration on food production: empirical evidence from 2,571 counties in China. *Front. Sustain. Food Syst.* 9:1679453. doi: 10.3389/fsufs.2025.1679453

Cui, N., and Dong, J. (2021). Grain production security in major grain-producing areas: status, challenges and guarantee path. *Iss. Agri. Econ.*, 7:130–144. doi: 10.13246/j.cnki.iae.2021.07.012

Cui, K., and Shoemaker, S. P. (2018). A look at food security in China. *Npj Sci. Food* 2:4. doi: 10.1038/s41538-018-0012-x

Elhorst, J. P. (2014). Matlab software for spatial panels. *International Regional Science Review*, 37, 389–405. doi: 10.1177/0160017612452429

FAO (2008). An introduction to the basic concepts of food security. Rome, Italy: FAO.

FAO (2021). The white/wiphala paper on indigenous peoples' food systems. Rome: FAO.

FSIN. (2025). Global report on food crises (GRFC) 2025. Available online at: https://www.fsinplatform.org/report/global-report-food-crises-2025 (Accessed November 3, 2025).

Gao, M., Mao, X., Wang, Z., and Feng, Y. (2025). The impact of digital village policy implementation on the innovation and establishment of new agricultural operators: evidence from China. *Front. Sustain. Food Syst.* 9:1650488. doi: 10.3389/fsufs.2025.1650488

Goldfarb, A., and Tucker, C. (2019). Digital economics. *J. Econ. Lit.* 57, 3–43. doi: 10.1257/jel.20171452

Gong, B., and Wang, S. (2021). The multi-channel effects of fiscal expenditure on China's agricultural growth. *Iss. Agri. Econ.*, 1:54–68. doi: 10.13246/j.cnki.iae.2021.01.006

Gong, Y., and Zhang, Y. (2023). Influence of well-facilitated capital farmland construction policy on grain productivity. *J. Hua. Agri. Univ. (Soc. Sci. Edn.)*, 4, 175–190. doi: 10.13300/j.cnki.hnwkxb.2023.04.018

Han, H., and Zhang, L. (2015). Analysis of the threshold effect of agricultural informatization on total factor productivity growth in agriculture. *Chin. J. Manage.*, 8:11–21. doi: 10.20077/j.cnki.11-1262/f.2015.08.002

Hayami, Y., and Vernon, R. (1985). Agricultural development: an international perspective. Baltimore, MD: Johns Hopkins University Press.

He, X. (2016). Thoughts on the scale of agricultural operations in our country. *Iss. Agri. Econ.* 37, 4–15. doi: 10.13246/j.cnki.iae.2016.09.001

He, L., and Zhang, X. (2022). Development of digital economy and technological upgrading of urban manufacturing: influence mechanism and empirical evidence. *Contemp. Econ. Res.*, 7:99–112.

Hong, M., Tian, M., and Wang, J. (2023). The impact of digital economy on green development of agriculture and its spatial spillover effect. *China Agric. Econ. Rev.* 15, 708–726. doi: 10.1108/CAER-01-2023-0004

Hou, D., and Wang, X. (2025). Can agricultural insurance enhance comprehensive grain production capacity? Mechanisms of risk protection and production incentives. *Front. Sustain. Food Syst.* 9:1649495. doi: 10.3389/fsufs.2025.1649495

Hu, P., and Liu, J. (2025). Mechanisms of improving agricultural ecological efficiency through digital village development and its empirical analysis. *China Popul. Resour. Environ.* 35, 162–173.

Hu, J., Xie, W., and Liu, M. (2025). How does digital village alleviate rural household energy poverty? *Energy* 318:134713. doi: 10.1016/j.energy.2025.134713

Hua, C., Lu, Q., Jiang, Y., and Woodward, R. (2013). Factors affecting farmers' participation on education and control program of agricultural non-point source pollution. *Soft Sci.* 27, 94–98.

Huang, Y., Tang, L., and Shang, Y. (2025). Pesticide reduction, climate change, and food security: evidence from rice production in China. *Front. Sustain. Food Syst.* 9:1669981. doi: 10.3389/fsufs.2025.1669981

Hussain, S. S., Byerlee, D., and Heisey, P. W. (1994). Impacts of the training and visit extension system on farmers' knowledge and adoption of technology: evidence from Pakistan. *Agric. Econ.* 10, 39–47. doi: 10.1111/j.1574-0862.1994.tb00287.x

Iganiga, B., and Unemhilin, D. O. (2011). The impact of federal government agricultural expenditure on agricultural output in Nigeria. *J. Econ.* 2:81–88. doi: 10.1080/09765239.2011.11884939

Jia, X., Huang, J., Xiang, C., Hou, L., Zhang, F., Chen, X., et al. (2013). Farmer's adoption of improved nitrogen management strategies in maize production in China: an experimental knowledge training. *J. Integr. Agric.* 12, 364–373. doi: 10.1016/S2095-3119(13)60237-3

Jia, X., and Zhu, T. (2025). Digital factors spur rural industrial integration: mediating roles of rural entrepreneurship and agricultural innovation in China. *Front. Sustain. Food Syst.* 9:1649953. doi: 10.3389/fsufs.2025.1649953

Jiang, T. (2022). Mediating effects and moderating effects in causal inference. *China Indus. Econ.*, 5:100–120. doi: 10.19581/j.cnki.ciejournal.2022.05.005

Jiang, W., Yan, T., and Zhang, J. (2021). Can internet use promote farmers to adopt straw returning technology?—an empirical analysis based on endogenous switching probit model. *J. Agrotech. Econ.*, 3:50–62. doi: 10.13246/j.cnki.jae.2021.03.004

Khan, M., and Damalas, C. A. (2015). Farmers' willingness to pay for less health risks by pesticide use: a case study from the cotton belt of Punjab, Pakistan. *Sci. Total Environ.* 530-531, 297–303. doi: 10.1016/j.scitotenv.2015.05.110

Li, H., Li, S., and Nan, L. (2017). Can technical training reduce pesticide overuse? *Chin. Rural Econ.*, 10:80–96. doi: 10.20077/j.cnki.11-1262/f.2017.10.007

Lin, Q., Dai, X., Cheng, Q., Lin, W., Lin, Q., and Dai, X. (2022). Can digital inclusive finance promote food security? Evidence from China. *Sustainability* 14:13160. doi: 10.3390/su142013160

Lin, L., and Zhu, Z. (2022). "Stabilizing employment" or "destroying employment"? The impact of digital economy on migrant workers' high-quality employment. *South China J. Econ.*, 12:99–114. doi: 10.19592/j.cnki.scje.400419

Liu, T., Qu, F., Jin, J., and Shi, X. (2008). Impact of land fragmentation and land transfer on farmer's land use efficiency. *Resour Sci*, 10:1511–1516.

Liu, M., Wang, J., and Li, H. (2025). Can farmers' digital economy participation promote their conservation tillage behavior under the perspective of agricultural industry chain? *Land Use Policy* 159:107776. doi: 10.1016/j.landusepol.2025.107776

Liu, Z., Xin, X., and Lv, Z. (2021). Does farmers' access to agricultural information on the internet promote the land transfer? *J. Agrotech. Econ.*, 10:100–111. doi: 10.13246/j.cnki.jae.2021.02.009

Liu, J., Yu, Q., Chen, Y., and Liu, J. (2022). The impact of digital technology development on carbon emissions: a spatial effect analysis for China. *Resour. Conserv. Recycl.* 185:106445. doi: 10.1016/j.resconrec.2022.106445

Lu, Z., Gou, D., Wu, Q., and Feng, H. (2025). Does the rural digital economy promote shared prosperity among farmers? Evidence from China. *Front. Sustain. Food Syst.* 9:1649753. doi: 10.3389/fsufs.2025.1649753

Lv, W., Zhang, X., and Wang, W. (2015). Subsidies for the purchase of agricultural machinery, agricultural production efficiency and the transfer of rural labor force. *Chin. Rural Econ.*, 8:22–32. doi: 10.20077/j.cnki.11-1262/f.2015.08.003

Marson, M. (2025). Effects of public expenditure for agriculture on food security in Africa. *Empir. Econ.* 68, 2673–2704. doi: 10.1007/s00181-025-02713-4

Ogutu, S. O., Okello, J. J., and Otieno, D. J. (2014). Impact of information and communication technology-based market information services on smallholder farm input use and productivity: the case of Kenya. *World Dev.* 64, 311–321. doi: 10.1016/j.worlddev.2014.06.011

Peng, J., and Huang, S. (2024). Mechanisms of digital technology's impact on grain yield from perspective of food security. *J. South China Agri. Univ. (Soc. Scie. Edn.)* 23, 77–92.

Rijswijk, K., Klerkx, L., Bacco, M., Bartolini, F., Bulten, E., Debruyne, L., et al. (2021). Digital transformation of agriculture and rural areas: a socio-cyber-physical system framework to support responsibilisation. *J. Rural. Stud.* 85, 79–90. doi: 10.1016/j.jrurstud.2021.05.003

Ruan, R., Zhou, P., and Zheng, F. (2017). The informatization development status and countermeasure suggestions for new agricultural business entities in the context of the "internet" — based on survey data from 1,394 new agricultural business entities nationwide. *J. Manag. World*, 7:50–64. doi: 10.19744/j.cnki.11-1235/f.2017.07.005

Shan, T., and Shi, R. (2025). Impact of digital village development on the urban–rural income gap—a spillover effects perspective. *Financ. Res. Lett.* 86:108557. doi: 10.1016/j.frl.2025.108557

Trendov, N. M., Varas, S., and Zeng, M. (2019). Digital technologies in agriculture and rural areas – Status report. Rome, Italy: FAO.

Wan, D., Peng, Z., and Li, L. (2023). Measuring and evaluating the integrated development level of digital economy and agriculture in China. *Chin. Rural Econ.*, 6:48–71. doi: 10.20077/j.cnki.11-1262/f.2023.06.004

Wang, Z., Chen, X., and Shi, L. (2025). Assessing the impact of Granary County subsidy program on county grain production in China: an analysis based on the spatial difference-in-differences model. *J Agrotech Econ*, 2:63–91. doi: 10.13246/j.cnki.jae.20240618.002

Wang, L., and Hou, W. (2024). Ideal or phantom: beyond the myth of optimal government size. *J. Peking Univ. (Philos. Soc. Sci.)* 61, 34–44.

Wang, P., Li, C., Huang, C., Wang, P., Li, C., and Huang, C. (2023). The impact of digital village construction on county-level economic growth and its driving mechanisms: evidence from China. *Agriculture* 13. doi: 10.3390/agriculture13101917

Wang, G., Lin, X., and Wang, J. (2025). How can digital new quality productive forces empower food security. *Reform Econ. Syst.*, 3:174–183.

Wang, Z., Liu, B., and Zhu, J. (2024). Effects of the digital economy on China's food system resilience. *J. China Agric. Univ.* 29, 261–275.

Wang, F., Sun, S., and Liu, T. (2023). Has the development of digital economy promoted changes in agricultural production methods? Evidence from prefectures in the Yellow River Basin. *Chin. Rural Econ.*, 9:122–143. doi: 10.20077/j.cnki.11-1262/f.2023.09.007

World Bank. (2021). World development report 2021: Data for better lives. World Bank Group. Available online at: http://documents.worldbank.org/curated/en/248201616598597113 (Accessed January 5, 2026).

Xia, X., Chen, Z., Zhang, H., and Zhao, M. (2019). Agricultural high-quality development: digital empowerment and implementation path. *Chin. Rural Econ.*, 12:2–15.

Xin, L., Gao, R., and Jiang, H. (2018). Evaluation of comprehensive grain production capacity in main grain-producing areas in China. *Chin. J. Agric. Resour. Reg. Plann.* 39, 37–45.

Xiong, C., Wang, Y., Wu, Z., and Liu, F. (2024). What drives the development of digital rural life in China? *Heliyon* 10:e39511. doi: 10.1016/j.heliyon.2024.e39511

Yang, J., Zhong, F., Chen, Z., and Peng, C. (2016). The impact of changes in rural labor prices and population structure on the grain planting structure. *J. Manag. World*, 1:78–87. doi: 10.19744/j.cnki.11-1235/f.2016.01.008

Yi, F. (2021). Digital skills, livelihood resilience and sustainable poverty reduction in rural areas. *J. South China Agri. Univ. (Soc. Scie. Edn.)* 20, 1–13.

Ying, R., and Zhu, Y. (2015). The impact of agricultural technical training on farmers' agrochemical use behavior: evidence from experimental economics. *China Rural Survey* 50–58:95. doi: 10.20074/j.cnki.11-3586/f.2015.01.005

Zeng, Y., Song, Y., Lin, X., and Fu, C. (2021). Some humble opinions on China's digital village construction. *Chin. Rural Econ.*, 4:21–35. doi: 10.20077/j.cnki.11-1262/f.2021.04.002

Zhai, X., Zheng, Y., and Gao, X. (2025). Digital tools for soil stewardship: how internet access drives farmland conservation in rural China? *Front. Sustain. Food Syst.* 9:1619689. doi: 10.3389/fsufs.2025.1619689

Zhang, X., Wan, G., Zhang, J., and He, Z. (2019). Digital economy，financial inclusion，and inclusive growth. *Econ. Res. J.* 54, 71–86.

Zhang, F., Wang, F., Hao, R., Wu, L., Zhang, F., and Wang, F. (2022). Agricultural science and technology innovation, spatial spillover and agricultural green development—taking 30 provinces in China as the research object. *Appl. Sci.* 12:845. doi: 10.3390/app12020845

Zhao, W., Liang, Z., Li, B., Zhao, W., Liang, Z., and Li, B. (2022). Realizing a rural sustainable development through a digital village construction: experiences from China. *Sustainability* 14:14199. doi: 10.3390/su142114199

Zhao, T., Zhang, Z., and Liang, S. (2020). Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban China. *J. Manag. World* 36, 65–76. doi: 10.19744/j.cnki.11-1235/f.2020.0154

Zhong, Y., Ba, X., and Chen, M. (2024). Theoretical construction and governance approaches for national food security in the new era. *Chin. Rural Econ.*, 2:2–19. doi: 10.20077/j.cnki.11-1262/f.2024.02.001

Zhou, Y., Qiu, Z., Jiang, S., and Liu, M. (2024). Development of the digital economy and common prosperity in rural areas: a collaborative perspective of e-commerce and digital finance. *Econ. Res. J.* 59, 54–71.

Zhu, Q., Bai, J., Peng, C., and Zhu, C. (2019). Do information communication technologies improve agricultural productivity? *Chin. Rural Econ.*, 22–40. doi: 10.20077/j.cnki.11-1262/f.2019.04.003

Zhu, H., and Chen, H. (2023). Measurement, spatial-temporal evolution and promotion path of digital village development in China. *Iss. Agri. Econ.*, 3:21–33. doi: 10.13246/j.cnki.iae.20220728.001

Zhu, D., Kong, X., and Gu, J. (2014). The irrational equilibrium of excessive pesticide application by farmers: evidence from farmers in southern Jiangsu, China. *Chin. Rural Econ.* 41, 17–29. doi: 10.20077/j.cnki.11-1262/f.2014.08.002

Zhu, J., Peng, H., Zhang, Z., Wang, J., and Gao, Y. (2025). Study on the impact of digital rural development on food security: an empirical analysis at the county level. *China Soft Sci.*, 5:79–91.

Zhu, D., and Ye, L. (2024). Agricultural new quality productive force in China: level measurement and dynamic evolution. *Stat. Dec.* 40, 24–30. doi: 10.13546/j.cnki.tjyjc.2024.09.004

Appendix

In the index construction process, this study uses the entropy weight method to assign weights to each indicator and construct a composite index. Let x_{ij} represent the raw value of the j-th indicator for the i-th sample ($j = 1, 2, \ldots, m$), and after standardization, it becomes x'_{ij}.

(1) Data Standardization:

For positive indicators:

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

For negative indicators:

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

Where $\max\left(x_j\right)$ and $\min\left(x_j\right)$ represent the maximum and minimum values of the j-th indicator across all samples.

(2) Calculate the Proportion of Each Indicator:

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

(3) Calculate the Information Entropy of the Indicator:

$$e_j = -\frac{1}{\ln\left(n\right)} \sum_{i=1}^{n} p_{ij} \ln\left(p_{ij}\right)$$

Where n is the sample size, and $0 \le e_j \le 1$.

(4) Calculate the Redundancy of Information Entropy:

$$d_j = 1 - e_j$$

(5) Calculate the Weight of Each Indicator:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

(6) Calculate the Composite Index:

$$\text{Index}_i = \sum_{j=1}^{m} w_j x'_{ij}$$

Where m is the number of indicators in the system.