Journal of Autonomous Intelligence (2024) Volume 7 Issue 5
doi: 10.32629/jai.v7i5.1633

ORIGINAL RESEARCH ARTICLE

Impacts of agricultural digitization on China's food security: A sustainability roadmap

Bing Hu[1,2], Tajul Ariffin Masron[1,*], Fan Yang[1]

[1] *School of Management, Universiti Sains Malaysia, Minden 11800, Malaysia*

[2] *School of Economics and Management, Zhoukou Normal University, Zhoukou 466000, China*

*** Corresponding author:** Tajul Ariffin Masron, tams@usm.my

ABSTRACT

Digital technology plays a crucial role in addressing the urgent issues of food security and green and sustainable development. This article innovatively constructs Agricultural Digital Transformation indicators based on relevant theories and literature. It examines the effect of agricultural digital transformation on the food security development level in 30 provinces between 2011 and 2020. Research indicates that agricultural digitization has a significant positive impact on food security. In the future, the Chinese government should improve agricultural digital infrastructure development, stimulate agricultural technical innovation, and give talent support for agricultural digitization.

Keywords: agricultural digitization; food security; system GMM; China

ARTICLE INFO

Received: 6 March 2024
Accepted: 8 April 2024
Available online: 14 September 2024

1. Introduction

Stabilizing the basic agricultural market and ensuring food security is particularly important[1]. China is a significant food consumer, and enhancing food security is critical to ensuring national security while improving people's livelihoods and well-being. Digital agriculture encourages the use of existing or developing cutting-edge technologies in agri-food production[2,3] to achieve the United Nations Sustainable Development Goals of poverty reduction, zero hunger, and climate change mitigation[4,5]. In response to the challenges posed by population expansion on food security, scholarly investigations and governmental initiatives have prioritized agricultural production efficiency[6]. Chinese agricultural and rural reform development achieved significant results in 2022, with an annual sowing area for grains reaching 1.775 billion mu (117 million hectares), total national grain output reaching 687 million tons an increase of 0.5% over the previous year maintaining above six hundred fifty million tons for eight consecutive years; Grain supply amounted to approximately 829 million tons. However, despite these remarkable achievements in producing more grains domestically, we still face many practical problems, such as reduced arable land resources available due to soil degradation, groundwater depletion, loss of labor force from farming communities, water pollution affecting irrigation sources, seed source safety issues[5]. Agricultural development urgently needs to change the way food is produced. The use of fewer pesticides, less water usage, more yield per acre, and greater environmental sustainability are all results of the digital transformation of agriculture[6].

In theory, Agricultural digitization is considered an essential way to achieve green growth in agriculture[7]. Agricultural digitization realizes a transformation from a production system dominated by machinery towards one supported by digital technology integrating interconnected intelligent digital technology into grain production operation consumption practice enhancing productivity efficiency sustainability[8,9]. Digital technology may provide digital and intelligent assistance for food production, facilitating change in food production techniques[1]. Empirically, Panel data from 31 Chinese provinces (2004-2020) examined the link between factor mismatch and high-quality agricultural development[10]. According to the study, the digital economy considerably aided high-quality agricultural growth. Understanding the link between grain production and economic development is key to national food security and regional coordination. This study analyzes spatial coordination using data from 2,012 counties (2000–2017)[11].The findings indicate that the advancement of digital technology activates the agricultural production factor market and enhances the degree of agricultural production resource allocation in major grain-producing areas. Digital Social Innovation (DSI) addresses social challenges through digital technology, playing a key role in promoting sustainable development[12].Using fixed effect models, intermediary effect models, and threshold models on prefecture-level city-level data from 2012 to 2020[1]. According to the findings, digital financial development has a considerable positive influence on boosting food security.

Previous research on the influence of digital technology on agricultural growth concentrated on digital technology enabling seed industry innovation[13]. Farmland building is made possible by digital technology, and farmland is the lifeblood of food production[14]. Digital technology benefits agricultural production by lowering input costs, management expenses, and transaction costs, as well as lowering costs and improving efficiency in agricultural production[15]. However, there is little research on using digital technologies to improve food security[1].

This article's marginal contribution reflects on three aspects: First, expanding on what constitutes Agricultural Digitalization at an Agricultural level; Second, using the entropy weighting method to measure provincial-level Agricultural Digitalization and food security levels in China, providing support for analyzing the heterogeneity of provincial grain security and proposing differentiated policies; Thirdly, through robustness tests and heterogeneity tests, further clarifying the internal mechanism of how agricultural digitization affects food security to provide relevant countermeasures for modernizing agriculture development under a digital background.

The rest of this article is organized as follows: Section 2 offers a review of past research. Section 3 provides the research methods, encompassing model specifications and estimation strategies. Empirical results are detailed in Section 4. Finally, Section 5 provides a summary of the article's key findings.

2. Literature review

The concept of "agricultural digitalization" pertains to the integration of sophisticated digital technologies—including but not limited to artificial intelligence, big data, robotics, unmanned aerial systems, sensors, and communication networks—via the Internet of Things into agricultural production systems[5]. Digital technology is applied to modern agriculture and improves production systems to meet the social and environmental requirements of the new era[16]. Agriculture digitization initiatives are not novel[15]. Before the year 2000, the Global Positioning System was already implemented in the agriculture sector[17]. However, an agreement about the effects of digitalization on food security has not yet been reached.

Some scholars show that digital agriculture positively impacts food security. Digital agriculture helps optimize resource allocation, reduce transaction costs, achieve economies of scale, address information asymmetry issues, improve agricultural productivity, and increase crop yields and quality as well as enhance production efficiency, ultimately contributing to food security[7,18–22]. Digital farming is becoming one of the most promising fields, driving the development of smart agricultural ecosystems. Precision agriculture, modern technology, and smart supply chains are key to achieving high-quality yields[23]. Digital agriculture can optimize resource allocation by analyzing weather conditions, soil conditions, and crop health in real time, directly impacting agricultural yields and promoting more informed decision-making processes[24,25]. Digital technology can enhance productivity by improving resource utilization[6]. Digital technology can enhance agricultural productivity and increase yield through precision planting and real-time data analysis[21,26]. By implementing precise input applications and closely monitoring the planting process, digitalization can improve the quality of agricultural products. The use of digital technologies, a feature of Agriculture 4.0, can help achieve more sustainable agriculture[24]. Agricultural digitization empowers farmers with data-driven decision-making capabilities at the micro level, thereby improving efficiency and productivity[8,18]. The dynamic interaction between Chinese food security and the digital economy[1,27]. They assert the digital economy can be critical in enhancing food security by improving efficiency and transparency in the food supply chain.

Some scholars repute that digitalization in agriculture may also have adverse effects[28]. The digitization of agriculture appears to generate or worsen divides between elites (those with clout in digital agri-food systems) and the farmer (those who lack control over digital technologies)[29]. Rotz et al.[30] deem that the significant gap in accessing digital agricultural technology could exacerbate existing digital divides and negatively impact food security, particularly in developing countries and marginalized communities. Digital technology will raise concerns about agricultural data privacy and ownership[31]. Agricultural digitization may exacerbate inequality issues, especially for small-scale farmers who lack opportunities for digital technology exposure[5]. This could endanger marginalized community stability by threatening their ability to access sufficient resources to meet basic needs. Digital technologies are controlled by a few individuals who continue to consolidate power[32]. Additionally, adopting digital technology in agriculture may lead to unemployment in the short term and trigger social and economic unrest[30,33].

Interestingly enough, some studies suggest that the impact of agricultural digitization on food security is insignificant[5,34]. Digital technologies have the potential to change agriculture significantly, their impact on food security depends on other factors such as physical infrastructure availability and institutional supportiveness[15]. Similarly, addressing potential socio-economic problems before implementing pure agricultural digitization might not solve food problems[5].

Many scholars have also conducted corresponding surveys regarding the research on factors affecting food security. Food security is closely related to economic growth and development[35]. Positive correlation between economic growth and food security[36]. As GDP per capita reflects economic prosperity and influences food supply and prices[37], China's booming per capita GDP indicates the potential for improving food security. The population, arable land, and industrial structure are directly related to the supply-demand dynamics and food security[38,39]. Population dynamics significantly impact food security. The challenges of feeding a growing global population[40]. In China, population pressure demands efficient and sustainable agricultural production through digitization[41].The impact of soil degradation on food production and stressed the necessity of sustainable land use[42,43].

Furthermore, urbanization, rural human capital, research and development, and market orientation may also affect food security outcomes[44]. Rapid urbanization led to changes in land-use policies affecting grain production[45]. Rand and human capital are critical for driving agricultural technological innovation, impacting grain production and security[46]. Rural human capital is an aspect yet to be fully explored. Rural population skills, knowledge, and abilities may influence the effectiveness of agricultural digitization. Finally, the degree of market orientation is considered a key factor influencing food security[47].

The most important feature of digital agriculture is using digital agricultural knowledge, technology, and information as major production aspects[48]. Agriculture's digitization has resulted in a deep integration of current information technology and agriculture, opening up a new route for the transformation and growth of traditional agriculture. There is currently no standardized structure for digital agriculture indicators. Some studies concentrate on indicators such as rural and village digital economies. Integrating primary, secondary, and tertiary industries is crucial for revitalizing rural economies and expanding farmers' income. Studying how the digital economy fosters this integration is especially important amid China's rapid digital growth[49]. The digital economy's impact on green agricultural development is vital for modernization. This study, using panel data from 30 Chinese provinces (2011–2020), explores its effects and mechanisms, offering insights for optimizing digital infrastructure and advancing high-quality agriculture[50]. This paper uses non-competitive input-output table data from China (2002–2017) to understand the integration trends between agricultural industries and the digital economy through fusion contribution and linkage indicators. It then employs the APL (Average Path Length) model to visually analyze the degree of association between the two industries and uses the grey relational analysis method to study the coordination between the digital economy and agricultural industry transformation[51]. Digital agriculture as "the amount of industrialization of digital agriculture, as well as the digital quality of agricultural entities"[50]. Information can be customized based on farmers' characteristics, and experiments, machine learning, and two-way communication can improve services. Advances in behavioral science help enhance information transmission and address adoption barriers for improved agricultural technologies. Mobile-based systems can boost field extension workers' productivity and accountability while enhancing supply chain functions. Realizing the potential of digital agriculture requires interdisciplinary collaboration, integrating insights from behavioral science, agriculture, economics, and data science[28].

The above topics are valuable resources for judging China's level of digital agricultural development. Existing research, however, does not properly address agricultural digitalization indicators, frequently assessing from the standpoint of physical infrastructure, such as information infrastructure and not paying enough attention to soft indicators such as human capital and technology application. Agriculture's digitalization demands a big quantity of high-quality individuals to drive it, with digital information and technological applications penetrating the whole agricultural growth process. As a result, this study selects 21 specific indicators from four aspects—digital infrastructure, digital industrialization, industry digitization, and digital talent—to collectively reflect the level of agricultural digitalization.

Food security is characterized by its systemic and complex structure, encompassing many aspects such as resources, the environment, technology, and human capital. Scholars all around the globe use a multi-indicator composite index to assess food security. Food and Agriculture Organization has four dimensions: availability, access, usage, and stability, offering a framework for comprehensive and rigorous evaluation of food security globally[52]. Official indicators such as the number and prevalence of undernourished persons, moderate and severe food insecurity, and malnutrition are often utilized to monitor and assess food security. Based on the average values of the four components or dimensions—food security supply index, food security access index, food utilization index, and food stability index—a composite food security index is constructed. This index is used to assess the level of food security development in 51 developing countries[39]. Using this paradigm to analyze food security in Chinese provinces from four perspectives: food supply security, food access security, food production stability, and food production sustainability[27]. In recent years, The Economist Intelligence Unit has published an annual Global Food Security Index study that scores 113 nations internationally on four dimensions: price, availability, food quality and safety, and natural resource resilience. China scored 74.2 in 2022, ranking 25th higher than the world average[53].

As China enters a new stage of development, both the local and international contexts for food security have changed fundamentally, and food security now has new implications and aims. China has shifted its emphasis from primarily on number to a dual emphasis on quantity and quality, with increasing emphasis on structure, resources, and the ecological environment. Previous research on food security indicator systems concentrated on food quantity security rather than food quality security, ecological and environmental security, economic security, and resource security, which no longer satisfy the evaluation needs under the present development plan. As a result, several academics have rebuilt the food security rating system. This study, based on China's agricultural economic data from 2001 to 2020, uses the entropy weight TOPSIS model to develop a food security evaluation system with 25 indicators. It focuses on the new connotations and objectives of food security at the new development stage, assessing the evolution and current status of China's food security[54]. The definition of food security has continually evolved, incorporating four main pillars: availability, access, utilization, and stability, which are crucial for policy development. This paper argues that it is time to formally update the definition of food security to include two additional dimensions proposed by expert panels: agency and sustainability[55]. Considering the high priority the Chinese government places on food security and China's developed transportation and logistics systems, this paper selects 32 indicators across four dimensions: quantity security, quality security, resource security, and ecological security, to build a comprehensive set of 32 specific indicators to measure food security in Chinese provinces.

Overall, these studies provide valuable insights into the multifaceted impacts of digital transformation on agriculture sustainability, productivity, and food security. However, the above studies did not consider two aspects. Firstly, there is still controversy regarding whether agricultural digitization will promote food security, and the mechanism of its impact on food security remains unclear. Secondly, existing research on agricultural digitization index evaluation is not comprehensive enough. It lacks unified indicators, and few scholars have investigated the impact of agricultural digitization sub-indicators on China's food security.

3. Model specification and variable selection

Model specification: The theory of information and communication technology posits that by implementing digital agricultural technology—such as sensors, the Internet of Things, and remote monitoring—agricultural production can be rendered more efficient and intelligent, consequently leading to an enhancement in food production and quality. According to innovation theory, digital transformation has enhanced the agricultural system's adaptability and risk resistance, stimulated innovation in agricultural output, and introduced new management, commercial, and technological models. The application of digital technology may aid in achieving agricultural sustainability and promoting the harmonious growth of agriculture and the natural environment through reducing resource waste and the enhancement of efficiency, according to the theory of sustainable development. This article is based on the above theoretical support, considering that the development of food security is a dynamic and gradual process with inertia and different from the actual situation of food security only to consider the impact of current agricultural digitization. This paper adds a lagged period of food security as an explanatory variable and uses provincial dynamic panel data to study how agricultural digitization affects food security. The baseline regression model constructed in this paper is shown below:

$$FS_{i,t} = \alpha_1 FS_{i,t-1} + \alpha_2 ADIG_{i,t} + \alpha_k Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{1}$$

Among them, i represents the region, t represents the period, $FS_{i,t}$ is the level of food security, and $FS_{i,t-1}$ represents the food security in region i during period $t-1$. $ADIG_{i,t}$ is the level of agricultural digitization, which is further divided into digital infrastructure ($ADIG1_{i,t}$), digital industrialization ($ADIG2_{i,t}$), industrial digitization ($ADIG3_{i,t}$), and digital talent ($ADIG4_{i,t}$). The estimated coefficient α_2 reflects its impact on food security and is expected to be positive. $Z_{i,t}$ represents a series of control variables that may affect food security, with α_k as their impact coefficients. μ_i and δ_t represent the province and time-fixed effects, respectively. In contrast, $\varepsilon_{i,t}$ is a random error term.

To obtain an index of agricultural digitization and food security, this paper adopts the entropy weight method to assign weights to indicators objectively[56]. At present, from the perspective of food security guarantee measures, China has shifted from focusing on the quantity of grain safety to both quantity and quality safety; From the perspective of food security goals, China has shifted from a comprehensive increase in grain production to ensure absolute food security[57]. According to the "National Food Security Medium and Long-term Plan (2008–2020)" and the "National Rural Revitalization Strategic Plan (2018–2022)", combined with the analytical framework and research results of the United States Department of Agriculture, FAO and the Economist Intelligence Unit, from 32 indicators are selected from the four dimensions of quantity security, quality security, resource security and ecological security, focusing on meeting China's food security requirements in the new era[22]. The dimension of quantity includes the total output of grains per unit area, grain yield per unit area, crop harvest fluctuation coefficient, per capita cereal production volume, indexes such as dependence degree on foreign trade, and domestic price indexes for cereals, and rural residents' disposable income per capita[58]. Quality dimensions include pesticide usage, fertilizer application rate, polyethylene film usage, and wastewater discharge. The dimension of resources includes arable land per capita, total water resources per capita, effective irrigated farmland area, financial expenditure on grain production, agricultural machinery power, total agricultural labor force, and agricultural labor productivity[58]. The dimension of ecology includes drainage areas, water-saving irrigation areas, crop disaster-prone areas, and total investment in environmental pollution control[58].

On the measurement of agricultural digitalization, there are mainly two methods for evaluating the level of digital development in rural areas: i) a single indicator method, which measures it by using a single indicator such as rural internet penetration rate, and proportion of mobile terminals in rural areas, per capita telecommunications consumption ratio in rural areas, and proportion of broadband users in rural areas; ii) the other is a comprehensive index method that evaluates regional agricultural digital development levels through constructing an evaluation system based on multiple indicators. Considering that the impact of agricultural digitization on food security is multidimensional and complex, it is impossible to fully measure the overall level of digital development with just one indicator alone. Therefore, we use a comprehensive index construction method to measure agricultural digitization by referring to the 2019–2020 China Digital Economy Development Index (CDEDI), reports from the China Academy of Information and Communications Technology (CAICT) published nationwide provincial-level plans for promoting information technology application across various industries and so on, focusing on examining the status quo regarding digital developments within agriculture sector while building up an integrated index system consisting 21 variables related to agricultural digitization using entropy weight calculation method to obtain composite indices reflecting overall progress made towards achieving goals set forth under national policies or guidelines.

First, digital infrastructure (ADIG1)[59]: As an essential material condition for economic growth driven by data accumulation sharing along with integration applications enabled via advanced communication networks technologies like fiber optic cables connecting remote regions with high-speed internet access points at local post offices serving average population density per village/township area covered by postal routes delivering mail/packages daily plus radio/TV broadcasting coverage rates averaged over all villages/towns surveyed–six variables are selected here.

Second, digital industrialization (ADIG2)[60]: Digital industrialization reflects the spillover effects of inter-industry development, which is a core driving force for economic and social progress. Six variables that best reflect digital industrial development are used here to represent it: per capita total telecom service volume, number of domain names registered, express delivery revenue, number of patents filed in the digital economy sector, and proportion of e-commerce enterprises engaged in online transactions and e-commerce sales.

Third, industry digitization (ADIG3)[61]: Agricultural digitization transformation involves monitoring and managing agricultural production while using available connectivity methods such as e-commerce platforms or social media networks to connect farmers with markets throughout the entire process from production through distribution and sales. The following indicators are used to measure this aspect: i) total area under facility agriculture/horticulture cultivation divided by arable land area; ii) number of meteorological observation stations serving rural areas; iii) proportion of agricultural products sold online channels like Taobao Villages; iv)average annual expenditure on various types life-related digital products/services consumed by rural households; v) mobile phone ownership rate per 100 households in rural areas; vi) broadband access penetration rate among all households living within rural regions.

Fourth, digital talent (ADIG4)[62]: Human capital is an endogenous driver for building infrastructure supporting agricultural digitization across its entire system/processes. A hundred internet users per capita, the average education level attained by residents living in rural areas, and employment figures related to the information transmission software/IT services industry working at urban units are selected as specific indicators reflecting overall progress toward achieving goals set forth under national policies or guidelines.

In order to reduce endogeneity caused by omitted variables, it is necessary to control for other factors that may affect regional food security beyond the level of digital development in agriculture[39]. Based on existing literature, this article selects eight indicators from social and economic factors, essential element endowment, and geographical climate as control variables for the model. Among them are i) economic development level, which is measured by using GDP per capita; ii) the population; iii) cultivated land area per capita; iv) industrial structure, which uses the proportion of primary industry output value to GDP; v) urbanization level, which is measured by the ratio of permanent urban population to total population; vi) technological innovation, which applies uses R&D internal expenditure as a percentage of fiscal expenditure in each province; vii) human capital, which is proxied by the rural education years per capita; viii) market-oriented degree, which uses Fan Gang's market-oriented index for its calculation.

Estimation technique: This paper adopts the GMM estimation method to solve the potential endogeneity issue. The Generalized Method of Moments (GMM) offers a novel approach to identifying instrumental variables (IVs). GMM can partially alleviate concerns related to bidirectional causality and omitted variable bias by utilizing lagged values of independent variables as IVs. This method mainly sets first-order difference variables in estimation equations as instrumental variables under certain assumptions to obtain difference GMM estimates, effectively solving endogeneity problems of explanatory variables. However, one disadvantage of the difference GMM methods is that it may lose some sample information.

Moreover, the explanatory variable's long-term continuity weakens the instrumental variable's effectiveness, especially for small samples. Therefore, we use the system-GMM estimation method[63], which introduces a horizontal equation based on the difference GMM estimation method adding a lagged-difference variable as an instrument for corresponding horizontal equation variable, significantly improving estimate validity results. In addition, using a two-step system-GMM can eliminate heteroscedasticity interference. We use a two-step system, the GMM estimation method, to conduct a regression analysis of the model.

Data source: This study selects provincial panel data from 30 provinces (municipalities, autonomous regions) for 2011–2020. Due to difficulties in data acquisition, our sample does not include Hong Kong, Macao, Taiwan, and Tibet. The data are sourced from the National Bureau of Statistics' 'China Statistical Yearbook', local government work reports, and statistical bulletins. The original data comes from the "China Rural Statistical Yearbook", "China Statistical Yearbook", "Statistical Report on Internet Development Status in China" and various provincial statistical yearbooks and public information. In order to eliminate the influence of prices, all currency-measured variables involved in this paper are converted into actual prices at 2000 through GDP deflator adjustment. At the same time, due to missing data for some provinces in specific years, missing data are supplemented through statistical yearbooks and bulletins at prefecture-level cities or interpolated if they still need to be included.

Table 1. The descriptive statistical results.

VarName	Obs	Mean	SD	Min	Max
FS	300	0.277	0.122	0.110	0.656
ADIG	300	0.135	0.090	0.046	0.620
PGDP	300	56,385.680	27,306.474	16,413.000	1.65e + 05
POP	300	4599.783	2837.845	568.000	12,624.000
LAND	300	3816.965	3073.114	46.500	14,438.400
IS	300	9.819	5.315	0.270	25.800
URB	300	0.590	0.122	0.350	0.896
RD	300	0.017	0.011	0.004	0.064
RHC	300	7.767	0.596	5.848	9.741
MA	300	7.941	1.892	3.359	11.934
FSS	300	0.308	0.137	0.071	0.792
FSQ	300	0.723	0.186	0.171	0.997
FSR	300	0.252	0.125	0.019	0.626
FSB	300	0.226	0.190	0.023	0.847

Table 1 presents the descriptive statistics for the variables. To ensure the credibility of the estimation results and mitigate the influence of data outliers, descriptive statistics were conducted on each variable. The results in **Table 1** revealed no outliers, and the multicollinearity tests showed that all VIF (variance inflation factor) values were less than 10, indicating the absence of multicollinearity issues and ensuring the data's statistical quality. As shown in **Table 1**, from 2011 to 2020, the standard deviation of each variable was smaller than its mean value, indicating the data's high stability. Regarding food security indicators, the mean value from 2011 to 2020 was only 0.277, suggesting a relatively low level of food security. As for agricultural digitalization indicators during this period, their mean value was only 0.135, with minimum and maximum values recorded at 0.046 and 0.620, respectively. This reflects significant disparities among Chinese provinces in terms of their agricultural digitalization development levels, which are still quite low overall.

4. Results and discussion

Correlation analyses are omitted but are available upon request to conserve space. This study uses a dynamic panel model to estimate the impact of agricultural digitization on food security, which requires autocorrelation and overidentification tests. In the autocorrelation test used to check the random disturbance term difference item, the p-values for first-order (AR(1)) and second-order (AR(2)) are less than 0.1 and more significant than 0.1, respectively, indicating that there is no high-order autocorrelation in the disturbance term difference item $\varepsilon_{i,t}$, and thus satisfying the premise of system GMM model estimation method, demonstrating that our estimation method is reasonable. Regarding the overidentification test, the Hansen value is 0.808, indicating no more instrumental variables than differences between virtual and exogenous variables; the covariance matrix remains full rank without the overidentification problem. Overall, this study's choice of dynamic panel model for testing is appropriate. Meanwhile, we report both one-step-difference GMM model results and two-step-system GMM model results for comparative empirical analysis with no systematic bias found in each estimation method.

We mainly focus on examining how agricultural digitization (ADIG) affects food security (FS). The regression results show that the coefficient of agricultural digitization (ADIG) is significant in all four models tested here. This means that agricultural digitization has a significant impact on food security. Specifically, when agricultural digitization increases, food security also increases. We will discuss mainly Model (1), the results of two-step-system GMM from **Table 2**. In this case, lags at first order for food safety are significantly positive at 1%, indicating a significant correlation between the current food safety levels and those of previous periods. Food security exhibits apparent path dependence and strong time continuity. Agricultural digitization significantly promotes food security and is also significant at the 1% level. Experimental results show that for every 1% increase in agricultural digitization, food security increases by 0.110%. Agricultural digitization treats digital technology as an input factor, which improves farmers' food production efficiency; moreover, it optimizes other input factors and produces multiplier effects on their efficiency, thus improving grain production technical efficiency and promoting food security.

In the two-step GMM model, from the estimation results of control variables, factors such as arable land, industrial structure, technological innovation, rural human capital, and urbanization significantly impact food security. As land is the foundation of food production, increasing arable land can improve grain yield and thus enhance food security. At the same time, industrial structure has been optimized in the process of agricultural digitization, and agricultural production methods and productivity have been improved to promote scale and production modernization, further promoting food security. With increased investment in technological innovation and further improvement in human capital, their positive promoting effects are verified. However, the population growth rate coefficient for economic growth and market-oriented coefficients are significantly negative. The population has a significant negative impact on food security, possibly due to the increasing demand for grain caused by population growth that affects food security. Meanwhile, with economic development and continuous improvement in market orientation, people's dietary habits have changed, leading to decreasing demand for grains but increasing demand for such as meat, eggs, dairy products, vegetables, and fruits, negatively impacting food safety.

Table 2. Results of agricultural digitization on sub-grain security [2-Step SGMM; *DV* = *FS*].

	FS	**FSS**	**FSQ**	**FSR**	**FSB**
	SYS-GMM	**SYS-GMM**	**SYS-GMM**	**SYS-GMM**	**SYS-GMM**
FS_{t-1}	0.806***	0.823***	0.913***	0.273	0.955***
	[15.46]	[14.51]	[21.12]	[1.42]	[45.92]
ADIG	0.110***	0.240***	0.282***	0.244**	0.222***
	[3.53]	[3.09]	[3.22]	[2.05]	[2.88]
URB	0.136***	0.013	0.093**	0.218*	0.228***
	[3.91]	[0.25]	[1.94]	[1.80]	[5.50]
RD	1.534***	0.730**	−3.420***	−2.307	−1.581***
	[3.68]	[−2.14]	[−3.32]	[−1.59]	[−3.58]
lnPGDP	−0.033***	−0.084***	−0.010	−0.026	−0.088***
	[−4.29]	[−7.99]	[−0.56]	[−0.72]	[−3.03]
lnPOP	−0.012**	−0.026	−0.016	−0.084*	0.005
	[−2.12]	[−1.35]	[−1.36]	[−1.72]	[0.31]
lnLAND	0.023***	0.040***	−0.009	−0.054	0.005
	[3.30]	[2.94]	[−0.85]	[−1.28]	[0.60]
lnIS	0.011**	−0.034***	−0.009	0.091***	−0.019
	[2.42]	[−3.45]	[−1.28]	[4.96]	[−1.61]
lnRHC	0.012***	0.253***	0.020	0.137	−0.036
	[0.26]	[4.19]	[0.37]	[1.35]	[−0.72]

Table 2. (*Continued*).

	FS	FSS	FSQ	FSR	FSB
	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
lnMAR	−0.030**	0.040	−0.004	0.058	0.019
	[−2.07]	[1.58]	[−0.24]	[1.27]	[0.52]
_cons	0.231*	0.329*	0.328	0.850	0.820**
	[1.74]	[1.69]	[1.42]	[1.22]	[2.32]
AR(1)	0.033	0.002	0.005	0.033	0.003
AR(2)	0.108	0.463	0.841	0.859	0.157
Hansen	0.808	0.368	0.442	0.516	0.392
Sample	300	300	300	300	300

Note: ***, **, and *indicates statistical significance at 1%, 5%, and 10% levels, respectively; the value in parentheses represent z-statistics.

To further examine the specific impact of rural digitization on food security, this section takes the four-dimensional index of food security (FSS for quantity safety, FSQ for quality safety, FSR for resource safety, and FSB for ecological safety) as dependent variables. It applies them to the two-step system GMM regression in formula (1) above. The results are shown in **Table 2**. It can be found that all coefficients of rural digitization are significantly positive, indicating that rural digitization is conducive to promoting all aspects of food security, including quantity safety, quality safety, resource safety, and ecological safety.

Considering that the measured grain security (dependent variable) in this paper takes values between 0 and 1, which meets the conditions of a restricted dependent variable model, we use the Tobit model to re-estimate Model (1) and conduct tests using fixed effects. **Table 3** shows the results of robust regression. The first column presents the estimation results of the Tobit model. Comparing the estimation results of both models, changing models does not affect the direction of influence on agricultural digitization coefficient estimates. The conclusion drawn from replacing models is consistent with that obtained from baseline results, replacement of independent variables, exclusion of samples from direct-controlled municipalities, and reduction of periods.

Table 3. Robustness test.

	(1)	(2)	(3)	(4)	(5)
	Tobit model	Replacement of DV	Replacement of IV	Exclusion of samples	Reduction of time periods.
FS_{t-1}	-	0.474***	1.024***	1.018***	1.010***
	-	[3.74]	[14.66]	[14.78]	[13.19]
ADIG	0.114***	0.097**	0.125***	0.101***	0.104***
	[5.35]	[1.91]	[3.71]	[3.68]	[2.61]
URB	0.032***	0.012	−0.051***	−0.047**	−0.049***
	[3.23]	[0.97]	[−2.80]	[−2.47]	[−4.30]
RD	−0.058	−0.092***	0.015	−0.000	−0.015
	[−1.64]	[−2.88]	[0.99]	[−0.05]	[−1.34]
lnPGDP	0.057***	0.019*	−0.019	0.003	0.003
	[6.60]	[1.64]	[−1.13]	[0.33]	[0.41]
lnPOP	−0.011	0.001	0.019*	0.025***	−0.008
	[−1.35]	[0.11]	[1.85]	[3.10]	[−1.36]

Table 3. (*Continued*).

	(1)	(2)	(3)	(4)	(5)
	Tobit model	**Replacement of DV**	**Replacement of IV**	**Exclusion of samples**	**Reduction of time periods.**
lnLAND	0.244***	0.013	0.152**	0.074	0.032
	[4.75]	[0.24]	[2.54]	[1.33]	[0.64]
lnIS	0.132	1.684***	−1.068	0.142	−1.323**
	[0.25]	[2.82]	[−1.27]	[0.17]	[−2.33]
lnRHC	0.028	−0.032	0.001	−0.047	0.011
	[0.78]	[−0.88]	[0.03]	[−0.96]	[0.22]
lnMAR	−0.016	−0.003	0.017	0.043*	0.086***
	[−1.36]	[−0.18]	[0.85]	[1.91]	[3.69]
Constant	−0.198	0.639**	0.418***	0.391**	0.436***
	[−0.57]	[2.08]	[2.98]	[2.46]	[3.01]
AR(1)	-	0.059	0.000	0.000	0.000
AR(2)	-	0.446	0.611	0.390	0.546
Hansen	-	0.975	0.958	0.685	0.529
Sample	-	270	270	234	180

Note: ***, **, and *indicates statistical significance at 1%, 5%, and 10% levels, respectively; the value in parentheses represent z-statistics.

Replacement of the measurement method for the dependent variable of food security. As there is more than one method to measure food security, this paper uses the entropy weight TOPSIS method to measure food security. It is used as a dependent variable in a two-step system GMM regression for robustness testing. The estimation results are shown in column (2) of **Table 3**. The sign and significance of the estimated coefficients are consistent with those of the benchmark regression, indicating that the results are robust. The second proxy is digital economic development level. Agricultural digitalization is essential to digital economic development, but its impact on rural areas is relatively macroscopic. Therefore, this paper replaces the agricultural digitalization index with a digital economy index. In column (3) of **Table 3**, the estimation results show that agricultural digitization significantly positively affects food security and that regression results are robust. The result in column (4) is conducted by excluding samples from municipalities directly under central government administration. Considering that municipalities directly under central government administration differ significantly from other provinces in terms such as non-agricultural labor force urbanization rate, agricultural policy support, level of agricultural economic development, and speed at which agriculture modernizes itself, Beijing, Chongqing, Shanghai, and Tianjin are excluded from our sample set leaving us with 260 samples for parameter estimation after controlling variables and fixed effects have been considered.

Results shown in column (4) of **Table 3** indicate that after considering control variables and fixed effects, the estimated coefficient for agricultural digitization was significantly positive at a 1% level. Finally, considering data missing between the years 2011–2012, partly due to a lack of information about e-commerce transactional activities enterprises within a comprehensive indicator system for measuring agriculture digitization levels along with large-scale disruptions caused by COVID-19 in 2020, this paper removes data from these three years and selects data between 2013–2019 for testing. Empirical results are shown in column (5) of **Table 3**, indicating that the results remain robust, i.e., agricultural digitization contributes to improving food security.

Table 4. Regression results for agricultural digitization [2-Step SGMM; DV: FS].

	ADIG	ADIG1	ADIG2	ADIG3	ADIG4
FS_{t-1}	0.806***	0.964***	0.440**	0.864*	1.027***
	[15.46]	[7.28]	[2.16]	[3.77]	[14.18]
ADIG	0.110***	0.061*	0.186*	0.091*	0.136**
	[3.53]	[1.69]	[1.86]	[1.88]	[2.28]
URB	0.136***	0.002	−0.013	−0.051	−0.073**
	[3.91]	[0.06]	[−0.33]	[−0.84]	[−2.38]
RD	1.534***	−0.012	−0.050	−0.005	−0.005
	[3.68]	[−0.65]	[−0.84]	[−0.20]	[−0.34]
lnPGDP	−0.033***	0.004	0.131***	0.003	−0.011
	[−4.29]	[0.18]	[3.04]	[0.13]	[−0.87]
lnPOP	−0.012**	0.006	−0.040	0.011	0.012
	[−2.12]	[0.39]	[−0.85]	[0.35]	[0.95]
lnLAND	0.023***	−0.129	0.487	0.188	0.227
	[3.30]	[−0.89]	[0.99]	[1.41]	[2.35]**
lnIS	0.011**	0.330	0.924	−0.122	−1.665
	[2.42]	[0.77]	[0.40]	[−0.07]	[−1.68]*
lnRHC	0.012***	0.151	0.320	0.071	−0.047
	[0.26]	[1.20]	[0.87]	[0.71]	[−0.54]
lnMAR	−0.030**	0.044	−0.228	−0.018	0.069**
	[−2.07]	[1.01]	[−1.28]	[−0.48]	[2.33]
_cons	0.231*	−0.287	−0.735	0.366	0.714**
	[1.74]	[−0.73]	[−0.62]	[0.52]	[2.45]
AR(1)	0.033	0.001	0.009	0.002	0.001
AR(2)	0.108	0.714	0.639	0.601	0.431
Hansen	0.808	0.212	0.997	0.641	0.975
Sample	300	300	300	300	300

Note: ***, **, and *indicates statistical significance at 1%, 5%, and 10% levels, respectively; the value in parentheses represent z-statistics.

In addition, **Table 4** shows the estimation results for four sub-indicators of agricultural digitization. The second column shows the impact of digital infrastructure on food security. The result indicates that the coefficient for digital infrastructure is significantly positive and effectively promotes food security. A potential explanation is that digital infrastructure promotes the digital revolution, accelerates the development of the information economy and digital level, drives high-quality development in agriculture, and thus promotes food security[22]. Columns three to five shows how industrial digitization, industrialization through technology adoption, and availability of skilled labor affect food safety, with all coefficients being significantly positive, indicating significant promotion towards achieving better levels of Food Security across all sub-samples tested within Agricultural Digitization.

Based on the above robustness tests, there is no systematic bias between the results of the robustness test and those of the benchmark model. Overall, this indicates that the empirical conclusions are reliable, and that agricultural digitization significantly promotes China’s food security.

Table 5. Sub-Analysis results for agricultural digitization and food security [DV: FS].

Variables	(1) Eastern	(2) Central	(3) Western	(4) Grain Production Area	(5) Grain Area Sales	(6) Balanced Production and Sales Area
FS_{t-1}	−0.711	−1.663	0.954***	0.188	−0.422	−0.832*
	[−0.90]	[−1.57]	[72.87]	[−2.12]	[−1.30]	[−1.75]
ADIG	0.554**	1.608*	0.166***	0.551**	0.192**	4.799**
	[2.49]	[1.73]	[6.59]	[2.07]	[2.30]	[2.11]
URB	0.146	−0.238	0.001***	0.006	0.001	0.411***
	[0.94]	[−1.38]	[10.06]	[0.09]	[0.01]	[3.66]
RD	−0.287	−0.213	-	0.023	0.126	0.449
	[−0.86]	[−1.40]	-	[0.22]	[1.10]	[0.92]
lnPGDP	0.108*	0.495**	-	0.211***	−0.176*	−0.880
	[1.84]	[2.55]	-	[2.61]	[−1.75]	[−1.59]
lnPOP	0.129	−0.007	-	0.107	0.159*	0.491***
	[0.96]	[−0.14]	-	[1.49]	[1.68]	[4.89]
lnLAND	−0.076	-	-	0.288	-	−7.460***
	[−0.22]	-	-	[0.51]	-	[−3.24]
lnIS	−3.746	11.811	−0.897***	2.983	-	-
	[−1.53]	[1.42]	[−5.64]	[0.76]	-	-
lnRHC	0.121	-	-	−0.393	-	2.194***
	[0.32]	-	-	[−1.09]	-	[3.12]
lnMAR	0.017	0.324**	-	−0.250*	0.047	0.763***
	[0.25]	[2.03]	-	[−1.93]	[0.54]	[3.65]
Constant	-	-	-	−0.979	-	−4.240**
	-	-	-	[−0.64]	-	[−2.55]
AR(1)	0.379	0.006	0.053	0.080	0.017	0.015
AR(2)	0.986	1.000	0.015	0.243	0.568	0.020
Hansen	0.999	0.906	0.376	0.984	0.990	0.999
Sample	99	72	99	117	63	90

Note: ***, **, and *indicates statistical significance at 1%, 5%, and 10% levels, respectively; the value in parentheses represent z-statistics.

Due to significant regional differences in China's east-west span, it is necessary to conduct a regional heterogeneity analysis of the role of agricultural digitization in promoting food security by dividing the country into three regions: East, Central, and West. The regression results for each region are shown in **Table 5**. Columns (1), (2), and (3) show estimates of the impact of agricultural digitization on food security in Eastern, Central, and Western regions, respectively, using a two-step system GMM regression model. The results indicate that agricultural digitization significantly positively affects food security in both Eastern and Central regions. Compared with the overall situation nationwide, coefficients in the Eastern region were higher than those in the Central region. However, both were higher than the national average, while the Western region showed insignificant results. This suggests that different directions and magnitudes have been demonstrated regarding how digital agriculture development affects food security across different regions; its promotion effect gradually weakens from East to Center while showing insignificant results in West Region due to regional heterogeneity.

In addition, due to noticeable regional differences in China's agricultural resource endowment as well as characteristics of grain production and sales based on the 2001 Grain Circulation System Reform Opinion, which divided 30 provinces/cities into three major functional areas: prominent grain-producing areas, main grain selling area; balanced production-sales area according to their characteristics, we examined heterogeneity effects by analyzing how digital agriculture impacts food safety within these areas.

Columns (4), (5), and (6) represent the results of digital agriculture's impact on food safety within the Main Grain Producing Area, Main Grain Selling Area, and Balanced Production-Sales Area, respectively. Through various tests, the coefficients of digital agriculture in the main grain-producing area and main grain-selling area are significantly positive at a 5% level. In contrast, the balanced production-sales area failed to pass the autocorrelation test. China's main grain-producing areas are mainly concentrated in the central hills and northeast regions, where the introduction of digital infrastructure has improved efficiency throughout local agricultural production, management, consumption, and other links; thus, digitization can play a better role. Main grain selling areas are mainly distributed along the southeast coastal region and some large cities where digital economy development is relatively advanced with a more apparent driving effect on agriculture. These regions have developed relatively quickly with higher agricultural digitization levels, significantly improving food security. In contrast, balanced production-sales areas generally focus on industrial and tertiary industry development rather than applying digitization to all aspects of agricultural production. Hence, its promotion effect on food safety is limited.

5. Conclusion

Overall, agricultural digitization is crucial to improving China's food security. The study shows that: 1) agricultural digitization has a significant positive impact on food security, which still holds after robustness tests such as model replacement settings and variable replacements; 2) concerning the sub-indicators of agricultural digitization, digital infrastructure, industrial digitization, and digital talent all demonstrate a noteworthy positive influence on food security; 3) the impact of agricultural digitization on food security displays regional heterogeneity, with greater potential for development in central and western regions when compared to the eastern regions.

Based on the study findings presented above, the following policy suggestions are made: First, the government should adopt a strategic plan for agricultural digitalization and elevate its significance in the national agenda. Simultaneously, we should follow the development trend and continue to invest in the infrastructure required for agricultural digitalization. We may aid regional digital growth by pushing new infrastructure developments like artificial intelligence and the Internet of Things (IoT). We must also firmly promote agricultural technology innovation by giving enough R&D money, encouraging scholars to perform in-depth studies on agricultural digitalization, and boosting technical growth.

Second, the government must address the development disparity between the eastern, central, and western areas. Digitization policies must consider regional disparities by providing policy support for underdeveloped areas with increased investment in their digital economy infrastructure to help them catch up with more developed areas while limiting the further expansion of this "digital divide." Regarding resource allocation, more help should be provided to central-western areas, such as more technical assistance or financing support, and technical people training, to promote their digital agricultural growth.

Finally, the government must properly employ the guiding function of policy instruments in the development of agriculture's digital transformation. To encourage firms to invest in the expansion of Agri-digitization, the government must employ legislative instruments such as tax breaks or financial subsidies. The government requires full consideration based on local conditions and industry-economic development requirements, rational planning focusing on different aspects of each region's Agri-digitization developments, the formation of a well-structured development pattern, and flexible developmental concepts. Meanwhile, laws should be established to secure agricultural data security, protect farmers' rights and interests, and promote healthy digital agriculture growth.

Author contributions

Conceptualization, BH and TAM; methodology, BH; software, BH; validation, BH, TAMK and FY; investigation, BH; resources, BH; data curation, BH; writing—original draft preparation, BH; writing—review and editing, TAM; supervision, TAM. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

1. Li X, Guan R. How Does Agricultural Mechanization Service Affect Agricultural Green Transformation in China? International Journal of Environmental Research and Public Health. 2023; 20(2): 1655. doi: 10.3390/ijerph20021655
2. Gebresenbet G, Bosona T, Patterson D, et al. A concept for application of integrated digital technologies to enhance future smart agricultural systems. Smart Agricultural Technology. 2023; 5: 100255. doi: 10.1016/j.atech.2023.100255
3. Sharma C, Pathak P, Kumar A, et al. Sustainable regenerative agriculture allied with digital agri-technologies and future perspectives for transforming Indian agriculture. Environment, Development and Sustainability.2024. doi: 10.1007/s10668-024-05231-y
4. Irajifar L, Chen H, Lak A, et al. The nexus between digitalization and sustainability: A scientometrics analysis. Heliyon. 2023; 9(5): e15172. doi: 10.1016/j.heliyon.2023.e15172
5. Lioutas ED, Charatsari C, De Rosa M. Digitalization of agriculture: A way to solve the food problem or a trolley dilemma? Technology in Society. 2021; 67: 101744. doi: 10.1016/j.techsoc.2021.101744
6. Fu W, Zhang R. Can Digitalization Levels Affect Agricultural Total Factor Productivity? Evidence From China. Frontiers in Sustainable Food Systems. 2022; 6. doi: 10.3389/fsufs.2022.860780
7. Shen Z, Wang S, Boussemart JP, et al. Digital transition and green growth in Chinese agriculture. Technological Forecasting and Social Change. 2022; 181: 121742. doi: 10.1016/j.techfore.2022.121742
8. Moysiadis V, Sarigiannidis P, Vitsas V, et al. Smart Farming in Europe. Computer Science Review. 2021; 39: 100345. doi: 10.1016/j.cosrev.2020.100345
9. Sroufe R, Watts A. Pathways to Agricultural Decarbonization: Climate Change Obstacles and Opportunities in the US. Resources, Conservation and Recycling. 2022; 182: 106276. doi: 10.1016/j.resconrec.2022.106276
10. Qin S, Han Z, Chen H, et al. High-Quality Development of Chinese Agriculture under Factor Misallocation. International Journal of Environmental Research and Public Health. 2022; 19(16): 9804. doi: 10.3390/ijerph19169804
11. Xie K, Ding M, Zhang J, et al. Trends towards Coordination between Grain Production and Economic Development in China. Agriculture. 2021; 11(10): 975. doi: 10.3390/agriculture11100975
12. Tim Y, Cui L, Sheng Z. Digital resilience: How rural communities leapfrogged into sustainable development. Information Systems Journal. 2020; 31(2): 323-345. doi: 10.1111/isj.12312
13. Balyan S, Jangir H, Tripathi SN, et al. Seeding a Sustainable Future: Navigating the Digital Horizon of Smart Agriculture. Sustainability. 2024; 16(2): 475. doi: 10.3390/su16020475
14. Wang N, Hao J, Zhang L, et al. Basic Farmland Protection System in China: Changes, Conflicts and Prospects. Agronomy. 2023; 13(3): 651. doi: 10.3390/agronomy13030651
15. Deichmann U, Goyal A, Mishra D. Will digital technologies transform agriculture in developing countries? Agricultural Economics. 2016; 47(S1): 21-33. doi: 10.1111/agec.12300
16. Hrustek L. Sustainability Driven by Agriculture through Digital Transformation. Sustainability. 2020; 12(20): 8596. doi: 10.3390/su12208596

17. Theiss A, Yen DC, Ku CY. Global Positioning Systems: an analysis of applications, current development and future implementations. Computer Standards & Interfaces. 2005; 27(2): 89-100. doi: 10.1016/j.csi.2004.06.003
18. Mendes JAJ, Carvalho NGP, Mourarias MN, et al. Dimensions of digital transformation in the context of modern agriculture. Sustainable Production and Consumption. 2022; 34: 613-637. doi: 10.1016/j.spc.2022.09.027
19. Michels M, Musshoff O. A tobit regression model for the timing of smartphone adoption in agriculture. Heliyon. 2022; 8(11): e11272. doi: 10.1016/j.heliyon.2022.e11272
20. Tadesse G, Bahiigwa G. Mobile Phones and Farmers' Marketing Decisions in Ethiopia. World Development. 2015; 68: 296-307. doi: 10.1016/j.worlddev.2014.12.010
21. Wolfert S, Ge L, Verdouw C, et al. Big Data in Smart Farming—A review. Agricultural Systems. 2017; 153: 69-80. doi: 10.1016/j.agsy.2017.01.023
22. Zhang F, Sarkar A, Wang H. Does Internet and Information Technology Help Farmers to Maximize Profit: A Cross-Sectional Study of Apple Farmers in Shandong, China. Land. 2021; 10(4): 390. doi: 10.3390/land10040390
23. S.S. VC, S. AH, Albaaji GF. Precision farming for sustainability: An agricultural intelligence model. Computers and Electronics in Agriculture. 2024; 226: 109386. doi: 10.1016/j.compag.2024.109386
24. Mendes JAJ, Carvalho NGP, Mourarias MN, et al. Dimensions of digital transformation in the context of modern agriculture. Sustainable Production and Consumption. 2022; 34: 613-637. doi: 10.1016/j.spc.2022.09.027
25. Mühl DD, de Oliveira L. A bibliometric and thematic approach to agriculture 4.0. Heliyon. 2022; 8(5): e09369. doi: 10.1016/j.heliyon.2022.e09369
26. Zhou X, Chen T, Zhang B. Research on the Impact of Digital Agriculture Development on Agricultural Green Total Factor Productivity. Land. 2023; 12(1): 195. doi: 10.3390/land12010195
27. Lee CC, Zeng M, Luo K. Food security and digital economy in China: A pathway towards sustainable development. Economic Analysis and Policy. 2023; 78: 1106-1125. doi: 10.1016/j.eap.2023.05.003
28. Fabregas R, Kremer M, Schilbach F. Realizing the potential of digital development: The case of agricultural advice. Science. 2019; 366(6471). doi: 10.1126/science.aay3038
29. Atanga SN. Digitalization of agriculture: How digital technology is transforming small-scale farming in Ghana. Agrarian, Food and Environmental Studies (AFES) [Master's thesis]. Submitted to Erasmus University; 2020.
30. Rotz S, Gravely E, Mosby I, et al. Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. Journal of Rural Studies. 2019; 68: 112-122. doi: 10.1016/j.jrurstud.2019.01.023
31. Rotz S, Duncan E, Small M, et al. The Politics of Digital Agricultural Technologies: A Preliminary Review. Sociologia Ruralis. 2019; 59(2): 203-229. doi: 10.1111/soru.12233
32. Mager A, Katzenbach C. Future imaginaries in the making and governing of digital technology: Multiple, contested, commodified. New Media & Society. 2021; 23(2): 223-236. doi: 10.1177/1461444820929321
33. De Baerdemaeker J, Hemming S, Polder G, et al. Artificial intelligence in the agri-food sector: Applications, risks and impacts. Panel for the Future of Science and Technology, EPRS; 2023.
34. Regan Á. Smart farming' in Ireland: A risk perception study with key governance actors. NJAS: Wageningen Journal of Life Sciences. 2019; 90-91(1): 1-10. doi: 10.1016/j.njas.2019.02.003
35. Masron TA, Subramaniam Y. Does Poverty Cause Environmental Degradation? Evidence from Developing Countries. Journal of Poverty. 2018; 23(1): 44-64. doi: 10.1080/10875549.2018.1500969
36. Abdul Manap NM, Ismail NW. Food Security and Economic Growth. International Journal of Modern Trends in Social Sciences. 2019; 108-118. doi: 10.35631/ijmtss.280011
37. Gandhi VP, Zhou Z. Food demand and the food security challenge with rapid economic growth in the emerging economies of India and China. Food Research International. 2014; 63: 108-124. doi: 10.1016/j.foodres.2014.03.015
38. Su F, Liu Y, Chen SJ, et al. Towards the impact of economic policy uncertainty on food security: Introducing a comprehensive heterogeneous framework for assessment. Journal of Cleaner Production. 2023; 386: 135792. doi: 10.1016/j.jclepro.2022.135792
39. Subramaniam Y, Masron TA, Azman NHN. Biofuels, environmental sustainability, and food security: A review of 51 countries. Energy Research & Social Science. 2020; 68: 101549. doi: 10.1016/j.erss.2020.101549
40. Godfray HCJ, Beddington JR, Crute IR, et al. Food Security: The Challenge of Feeding 9 Billion People. Science. 2010; 327(5967): 812-818. doi: 10.1126/science.1185383

41. Lu S, Lu W, Xu M, et al. Water-energy-food security under green finance constraints in Southwest China. Energy Economics. 2023; 118: 106478. doi: 10.1016/j.eneco.2022.106478
42. Bindraban PS, van der Velde M, Ye L, et al. Assessing the impact of soil degradation on food production. Current Opinion in Environmental Sustainability. 2012; 4(5): 478-488. doi: 10.1016/j.cosust.2012.09.015
43. Gomiero T. Soil Degradation, Land Scarcity and Food Security: Reviewing a Complex Challenge. Sustainability. 2016; 8(3): 281. doi: 10.3390/su8030281
44. Svensson J, Yanagizawa D. Getting Prices Right: The Impact of the Market Information Service in Uganda. Journal of the European Economic Association. 2009; 7(2-3): 435-445. doi: 10.1162/jeea.2009.7.2-3.435
45. Liu Y, Zhou Y. Reflections on China's food security and land use policy under rapid urbanization. Land Use Policy. 2021; 109: 105699. doi: 10.1016/j.landusepol.2021.105699
46. Saiz-Rubio V, Rovira-Más F. From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. Agronomy. 2020; 10(2): 207. doi: 10.3390/agronomy10020207
47. Fusco G, Coluccia B, De Leo F. Effect of Trade Openness on Food Security in the EU: A Dynamic Panel Analysis. International Journal of Environmental Research and Public Health. 2020; 17(12): 4311. doi: 10.3390/ijerph17124311
48. Klerkx L, Jakku E, Labarthe P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS: Wageningen Journal of Life Sciences. 2019; 90-91(1): 1-16. doi: 10.1016/j.njas.2019.100315
49. Zhang Z, Sun C, Wang J. How Can the Digital Economy Promote the Integration of Rural Industries—Taking China as an Example. Agriculture. 2023; 13(10): 2023. doi: 10.3390/agriculture13102023
50. Jiang Q, Li J, Si H, et al. The Impact of the Digital Economy on Agricultural Green Development: Evidence from China. Agriculture. 2022; 12(8): 1107. doi: 10.3390/agriculture12081107
51. Leng X, Tong G. The Digital Economy Empowers the Sustainable Development of China's Agriculture-Related Industries. Sustainability. 2022; 14(17): 10967. doi: 10.3390/su141710967
52. FAO. Thinking about the future of food safety. A foresight report Rome. 2022. doi: 10.4060/cb8667en
53. Bao Y, Leung MK, Poon D, et al. Integrating vertical farm into low-carbon high-rise building in high-density context: A design case study in Hong Kong. Journal of Building Engineering. 2024; 96: 110472. doi: 10.1016/j.jobe.2024.110472
54. Zhang X, Wang Y, Bao J, et al. A Research on the Evaluation of China's Food Security under the Perspective of Sustainable Development—Based on an Entropy Weight TOPSIS Model. Agriculture. 2022; 12(11): 1926. doi: 10.3390/agriculture12111926
55. Clapp J, Moseley WG, Burlingame B, et al. Viewpoint: The case for a six-dimensional food security framework. Food Policy. 2022; 106: 102164. doi: 10.1016/j.foodpol.2021.102164
56. Wang J, Dong K, Dong X, et al. Assessing the digital economy and its carbon-mitigation effects: The case of China. Energy Economics. 2022; 113: 106198. doi: 10.1016/j.eneco.2022.106198
57. Erokhin V, Tianming G, Chivu L, et al. Food security in a food self-sufficient economy: A review of China's ongoing transition to a zero hunger state. Agricultural Economics (Zemědělská ekonomika). 2022; 68(12): 476-487. doi: 10.17221/278/2022-agricecon
58. Guo Y, Wang J. Identifying the Determinants of Nongrain Farming in China and Its Implications for Agricultural Development. Land. 2021; 10(9): 902. doi: 10.3390/land10090902
59. Zhang H, Guo K, Liu Z, et al. How has the rural digital economy influenced agricultural carbon emissions? Agricultural green technology change as a mediated variable. Frontiers in Environmental Science. 2024; 12. doi: 10.3389/fenvs.2024.1372500
60. Peng J, Zhou M, Yi M, et al. Unveiling the impact of digital industrialization on synergistic governance of pollution and carbon reduction in China: a geospatial perspective. Environmental Science and Pollution Research. 2023; 31(25): 36454-36473. doi: 10.1007/s11356-023-31225-w
61. Attaran M. The impact of 5G on the evolution of intelligent automation and industry digitization. Journal of Ambient Intelligence and Humanized Computing. 2021; 14(5): 5977-5993. doi: 10.1007/s12652-020-02521-x
62. Gilch PM, Sieweke J. Recruiting digital talent: The strategic role of recruitment in organisations' digital transformation. German Journal of Human Resource Management: Zeitschrift für Personalforschung. 2020; 35(1): 53-82. doi: 10.1177/2397002220952734

63. Blundell R, Bond S. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics. 1998; 87(1): 115-143. doi: 10.1016/S0304-4076(98)00009-8