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The impact of digital capability on agricultural product sales: evidence from China

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Digital capability is a crucial skill for farmers' output in the context of the digital economy, and the marketing of agricultural products has long been a significant topic in agricultural economic studies. This study measures the level of digital competence of farm households from three dimensions—digital access conditions, digital information acquisition ability, and digital application ability—based on data from the 2020 China Rural Revitalization Survey (CRRS). It also empirically investigates the mechanism of the role of digital competence on the sale of agricultural products. In contrast to previous research that just looks at green transformation or production efficiency, this study employs a dual mediation model to show the intricate relationships between digital capabilities and agricultural product sales. The results show that raising farmers' level of digital competency can effectively boost sales of agricultural products; this effect is particularly noticeable for young farmers, large-scale farmers, and farmers in hilly areas. The mechanism analysis also demonstrates that increasing farm households' digital capabilities can boost agricultural product sales through two different avenues: increasing agricultural production efficiency and encouraging farmers to practice green production to improve the quality of their products, which will increase sales revenue. The paper's findings highlight the significance of digital competency in agricultural development and urge farmers to be able to capitalize on digital rural development opportunities to increase their revenue.

KEYWORDS

digital capability, agricultural products, sales, income, farmers

1 Introduction

China's modernization approach is based on the three rural challenges (Long et al., 2019). Since the countryside makes up over 90% of China's land and is the primary location of the nation's natural resources, including wetlands and water sources, agriculture is "the most important country" and provides a crucial economic basis for ensuring national food security in China. Farmers are one of the largest groups in China, and their level of development affects the livelihoods of the populace, social stability, and the country's ability to develop sustainably. However, China has seen a significant decline in its rural population recently, and the growth of rural agriculture has been hampered by a lack of human resources and a poor market link. To address these issues, the Chinese government has proposed a digital village strategy to help farmers overcome information barriers, achieve efficient market connections, and enhance the environment of agricultural product sales through digital technology. The strategy also aims to encourage talented individuals to return to their hometowns by building digital villages. Sales of agricultural products are crucial to agricultural and rural development since they are the primary source of revenue for farmers (Zhang et al., 2023). The primary player in the sales of agricultural products is the farmer, and the Digital Rural Action Plan (2022–2025) makes it abundantly evident that it is important to support rural residents' mastery and use of digital technology. This ability equips farmers with the knowledge and skills to use digital platforms and the Internet, and it encourages their participation in the creation of the digital countryside and the acquisition of the digital dividend. This will increase farmers' endogenous development motivation and improve their ability to sell agricultural products.

One of the primary objectives of rural revitalization has always been raising farmers' incomes. Numerous studies have demonstrated that agricultural sales revenue, a significant source of farm household income, not only contributes to farmers' income growth but also helps to revitalize rural resources and advance agricultural development (Tambo and Wünscher, 2017; Arham et al., 2020). Nevertheless, the portion of farmers' income that comes from the sale of agricultural products is declining yearly, and relevant data shows that in 2023, this portion only account for 22% of China's rural people' overall income. Additionally, the development of agriculture is beset by issues like the ongoing outflow of factors of production and the lack of adequate industrial integration. Currently, one of the key concerns in addressing the "three rural issues" is how to guarantee a rise in farmers' income while encouraging the sustainable growth of rural agriculture.

The establishment of digital villages has stimulated rural development by increasing the use of digital platforms and technology in communities. The majority of research has found that the adoption of digital technology contributes to the increase in farmers' incomes (Li and Jiang, 2023). On the one hand, digital technology's advancements in communication tools can assist farmers in expanding their avenues for agricultural product sales (Shimamoto et al., 2015), boost agricultural product sales via Internet access (Obare, 2013), and minimize information gaps to try to mitigate farmers' production and management risk and minimize some needless losses in the production and marketing process, which will make it easier for farmers to sell their produce (Jensen, 2007). Conversely, digital technology enables rural residents to access employment information, understand employment opportunities, acquire additional revenue streams, boost non-farm income, and ultimately raise farmers' overall income level (Ma et al., 2020; Zheng et al., 2023; Wang et al., 2023). On the other hand, some academics contend that the contribution of digital technology to farmers' income has been exaggerated. Leroux et al. (2001) contend that there are two obstacles to the adoption of digital technology in rural areas: first, farmers' digital literacy and education levels have a direct impact on their capacity to use information technology; and second, there is a notable disparity between the high cost of information infrastructure inputs and the degree of agricultural business efficiency improvement that has occurred thus far. Additionally, Yuan and Luo (2025) demonstrated that there is a significant group variability in the promotion of e-commerce in rural areas on the improvement of farmers' income, with the income-boosting effect primarily concentrated in the younger and economically better-off groups of farmers. Reuschke and Mason (2022) found that digital technology has no significant effect on the improvement of sales income of household chit. Farm households' income discrepancies are likewise expected to widen as the digital economy grows (Clark and Gorski, 2002). Furthermore, other academics have contended that the degree of digitization and rural incomes in China have an "inverted U-shaped" relationship (Evans, 2018) and that certain conditions limit the contribution of digital technology to rural earnings. The impact of digital technology on farmers' income can be directly impacted by how well-equipped rural residents are to use it. There is a rather little body of research on rural households' digital capacity, with most of it concentrating on the meaning of digital capacity profile and how it is measured. Digital competence, which typically encompasses cognitive, application, and innovative skills, is the ability to use digital, information, and communication technology (Bawden, 2001; Brandtzæg et al., 2011).

This paper has a strong theoretical basis thanks to the related research on digital technology and farmers' income, but there is still room for improvement in the study of how farmers' digital capabilities affects the sale of agricultural products, which gives this paper a chance to go deeper.

Does increasing the revenue from the sale of agricultural products have anything to do with farm households' ability to adopt technology? Which mechanism of action is at play here? In the process of developing digital villages and rural revitalization, this is a crucial and pressing subject. The immediate effect of farmers' digital proficiency on agricultural sales, however, has not received much attention in research. The mechanism of the agricultural Internet model on raising farmers' income level from three perspectives—farmers' characteristics, platform cognition, and social environment—was quantitatively investigated by Fang et al. (2020) using a logistic regression model. Cheng et al. (2024) investigated how digital skills may affect farmers' agricultural entrepreneurship and its possible mechanism. They also confirmed that farmers' digital skills could increase their revenue from a non-farm income standpoint.

Actually, the agricultural sector's innovation and the improvements in the business climate brought about by farmers' increased digital proficiency have made it easier to sell agricultural products. Gaining proficiency in digital skills might, on the one hand, assist farmers in expanding their sales channels, precisely matching consumer demand, and decreasing stagnating sales of agricultural products. Farmers can use the e-commerce platform to sell their products directly to consumers while also establishing their brand and increasing the repurchase rate through webcasting. They can use the big data platform to analyze customer needs, make accurate planting decisions, and lower the risk of agricultural product sales stagnating (Liu et al., 2024). On the other hand, production costs can be successfully decreased through the expert use of digital products and intelligent machinery. To lessen losses brought on by price swings, operate smart machinery, increase production efficiency, and keep an eye on apps relating to agricultural products. This research aims to discover the intrinsic mechanisms of the digital economy and analyze its income-generating effects from the standpoint of farmers' agricultural revenues.

This paper's potential marginal contributions include: First, by focusing on farmers' perspectives and closely analyzing how farmers' digital capabilities affect agricultural product sales, this study not only broadens the scope of the analysis of the impact of the policy assessment on digital village construction, but also enhances the quantitative foundation of the policy's evaluation. Second, we investigate how farmers' digital capacity influences agricultural product sales theoretically. Using the mediation model, we examine increasing agricultural production efficiency and encouraging farmers to practice green production effects on farmers' digital capacity impact agricultural product sales. Based on the baseline analysis, this paper uses farmers' age, farm business scale, and village topography to test the differences in farmers' digital capability to promote agricultural product sales. This will help to further investigate the impact of farmers' digital capability on agricultural product sales. The execution of digital village policies and the advancement of "agriculture, rural areas, and farmers" development are theoretically supported by these investigations and testing, which also serve as a guide for the government as it develops focused programs for the growth of the rural digital economy. The remainder of the paper is structured as follows: the theoretical mechanisms is covered in the second part; the research design is introduced in the third part; and the impact of farmers' digital competency on agricultural product sales is empirically analyzed in the fourth part using baseline regression, robustness testing, mechanism testing, and heterogeneity testing. Research findings and policy implications are presented in the final section.

2 Theoretical analysis and research hypotheses

Farmers' digital capabilities refer to their ability to effectively utilize digital technology in agricultural production, management, and social participation. It mainly includes digital access conditions, digital information acquisition, and digital application capabilities. Digital access conditions refer to the basic conditions for farmers to obtain digital information in agricultural production, operations, and social participation. They form the foundation of digital literacy and are a prerequisite for accessing digital information and applying digital technologies. Digital information access refers to farmers' ability to effectively search for, filter, and understand the information they need in a digital environment. It constitutes the intermediate layer of digital literacy and determines whether farmers can effectively apply digital tools, serving as a solid foundation for digital application capabilities. Digital application capability refers to farmers' ability to use digital technology to solve specific problems, representing the advanced layer of digital capability and reflecting the actual value of digital technology. Enhancing farmers' digital capability is not just a technical problem; it is also a crucial step toward economic empowerment, which is crucial for rural development.

2.1 A theoretical examination of how digital capabilities influence agricultural sales directly

According to Schultz, farmers' digital capabilities have given agricultural production a new kind of human capital that can optimize production methods, enhance the environment for the circulation of agricultural products, and boost the efficiency of the entire agricultural industry chain to increase agricultural sales income (Rijswijk et al., 2019). First of all, rural residents' lifestyles have changed as a result of their access to relevant digital devices, such as the Internet. The improvement of digital access capacity aids farmers in learning and mastering digital technology through digital infrastructure platforms, scientific sowing, scientific fertilizer application, precise production, cost reduction, and increased efficiency (Guo et al., 2023). Second, by removing market information asymmetry and optimizing production choices, digital information past capabilities greatly increase the revenue from agricultural sales (Siaw et al., 2020). Farmers may successfully connect to high-value channels, dynamically modify planting structures, and precisely understand the timing of sales when they have real-time access to price, supply and demand, and technological information. According to research by the Chinese Academy of Agricultural Sciences (CASA), farmers' market response time increases by 40% for every level of information accessibility, the risk of slow marketing decreases by 28%, and sales revenue immediately increases by 15–35%. Farmers' increased ability to access digital information creates a seamless marketing environment for the distribution of agricultural goods. Lastly, by enhancing operational efficiency, precisely linking to markets, and optimizing production management, the use of digital applications greatly raises agricultural sales revenue (Zhang and Fan, 2023; Marshall et al., 2020; Xie et al., 2021). Farmers who are adept at using e-commerce platforms and live-streaming tools can reach consumers directly, cut down on intermediate losses, and gain brand premiums. Farmers who are proficient with smart agricultural equipment can also improve product quality while reducing production costs by 20–30%. Sales of agricultural products are positively impacted by the improvement of digital application capabilities, which helps to increase the efficiency of the entire agricultural industry chain. Accordingly, research hypothesis H1 is put forth in this study.

> *H1*: Farmers' digital capabilities can effectively promote agricultural product sales, increase farmers' operating income, and promote agricultural development.

2.2 Analysis of the mechanism of the role of digital capabilities in influencing the sale of agricultural products

Increasing agricultural production efficiency mechanisms. Through precision agriculture technology, digital capacity dramatically increases production efficiency, which boosts agricultural products' market competitiveness and increases sales revenue. On the one hand, farmers' digital capacity is a new form of human capital that is employed as an input variable in the agricultural production function. It has a direct impact on the output of agricultural products, which in turn has an indirect impact on crop sales revenue. The enhancement of digital capacity facilitates farmers' accurate and efficient access to and processing of information pertaining to agricultural output. With this information, farmers may optimize the allocation of production elements and modify the production structure in real time to satisfy market demands. Higher digital capacity also helps farmers become more adept at using and understanding intelligent agricultural production equipment (Parra-López et al., 2025; Njuguna et al., 2025). This increases the value of their labor and lowers production costs, which boosts production efficiency and raises revenue from the sale of agricultural products. Higher digital capabilities, on the other hand, allow farmers to use digital technology and network platforms more effectively, expand their social networks, boost trust among social network subjects, improve their social capital, and lower the transaction costs of their participation in the market for productive capital. At the same time, the improvement of digital capabilities makes it easier for farmers to use At the same time, the improvement of digital capabilities makes it easier for farmers to use digital financial tools to ease financial difficulties and boost productive investment (Kelikume et al., 2021 Fu et al., 2024), which in turn helps to improve agricultural production efficiency and, ultimately, agricultural marketing performance. Consequently, it is suggested that:

> *H2*: By increasing the efficiency of agricultural production, digital capabilities successfully support the sale of agricultural products.

A mechanism for improving green quality. By encouraging green production practices, digital capabilities greatly increase agricultural sales revenue (Chen et al., 2023; Shen et al., 2022). As "rational economic beings," farmers will weigh costs and advantages while making decisions about output, ultimately aiming to maximize benefits. Enhancing digital capacity allows farmers to learn more scientific production techniques based on crop and land conditions, including precise irrigation, fertilizer, medicine, and sowing (Iost Filho et al., 2020). This reduces waste of water, fertilizer, and pesticides and converts cost savings into improved agricultural product quality, which raises the price of agricultural products per unit. However, greater digital capacity enables farmers to make better decisions and share information more easily, enhancing their ecological cognition (Gong et al., 2024). This helps to boost sustainable revenue from the sale of agricultural products and support the sustainable growth of agriculture (Wijerathna-Yapa and Pathirana, 2022). Simultaneously, farmers with strong digital skills can use digital platforms to precisely match consumers' green demands, offer traceability services for agricultural products, boost sales of related agricultural products, and raise the unit price of agricultural products through digital platforms like Jitterbug, all of which increase revenue from agricultural product sales. In conclusion, research hypothesis H3 is put out in this paper:

> *H3*: By influencing farmers' green production practices, digital capabilities successfully increase the sales of agricultural products.

3 Research design

3.1 Modeling approach

3.1.1 Ordinary least square method

This study builds a model of the effect of digital capability on agricultural sales revenue in order to confirm the relationship between the two and rely on pertinent research findings. Given that the sales revenue of agricultural products serves as the explanatory variable, this paper primarily builds a linear regression model and uses the ordinary least squares (OLS) estimation method to analyze the factors that influence sales revenue. The benchmark model is set as follows:

$$Income = \alpha_0 + \alpha_1 X_i + \alpha_2 CV_i + \varepsilon_i \quad (1)$$

Where income is the value of agricultural sales revenue after taking the logarithm to ensure the smoothness of the model, X is the digital capacity of the farmers, CV including individual characteristics, household characteristics and other control variables, and ε is the random perturbation term. The specific measurement methods for the indicators are described in detail in the next section on variable selection.

3.1.2 Mediating effect model

In order to overcome the limitations of the original mediating effect analysis method, this paper builds on Ting's (2022) proposal for a mediating effect operation to discuss the mechanism of the role of digital capacity on farmers' business income and to explore the impact of production efficiency and green behavior on farmers' business income in the theoretical analysis. In the subsequent empirical analysis, only the impact of digital capacity on production efficiency and green behavior is examined. Model 2 is built using Model 1 as a base, and it is configured as follows:

$$M_i = b_0 + b_1 X_i + b_2 CV_i + \varepsilon_i \quad (2)$$

Where M_i is the mediating variable, denoting production efficiency and green production behavior respectively, X is the numerical capacity of the farmers, CV including individual characteristics, household characteristics and other control variables, and ε is the random perturbation term. The specific measurement methods for the indicators are described in detail in the next section on variable selection.

3.2 Variable selection and data description

Explained variables. The explained variable of this paper is the income from the sale of agricultural products, which mainly includes the income from the sale of agricultural products related to planting, farming, forestry and fruit industry and fishery. Considering the problem that a large gap in the income from the sale of agricultural products of different families may lead to a large sample variance (Chen et al., 2014), the income from the sale of agricultural products is logarithmically treated.

Explanatory variables. The core explanatory variable of this paper is digital capacity. Combined with the actual life situation of farmers, referring to the studies of Gong et al. (2024) and Li et al. (2024), the index system of digital capacity of farmers is constructed from three aspects of digital access capacity, digital information acquisition and digital application capacity, as shown in Table 1. The indicators in the digital literacy index system for farmers are selected based on their actual production and living conditions, using on-site questionnaire surveys. Digital access conditions form the foundation for enhancing digital literacy, with smartphones and network infrastructure serving as the basic hardware for digital access. Therefore, digital access capability is assessed through three questions in the questionnaire: "Do you have a computer at home?" "Do you use a 4G/5G smartphone?" and "Is your household's internet connection very good?" These three questions are used to assess digital access capability. Digital information access is a concrete manifestation of farmers' participation in digital life. Therefore, digital information access is measured through the questionnaire question, "Do you wish to access information via your phone or the internet?" "Can you promptly access the information you prioritize?" "Can you access relevant information anytime via your phone or the internet?" Digital application capability refers to farmers' specific behaviors in solving problems, which is the most direct manifestation of their digital capabilities. Therefore, it is measured through the following questions in the

TABLE 1 Measurement of digital capability.

Variable	Variable classes	Judgment criteria
Digital capabilities	Digital access conditions	Do you have a computer?
		Do you use 4G/5G phones?
		Whether your home network is very good
	Digital information acquisition ability	Whether you want to follow information through your phone or the Internet
		Whether the information you focus on can be obtained in a timely manner
		Whether you can access relevant information at any time through your mobile phone or the Internet
	Digital application ability	Whether you have no difficulty using a 4G/5G phone
		Do you communicate important public affairs in the village through WeChat groups?
		Do you prefer the village committee to communicate information through WeChat and other network means
		Whether your family business has products traded online
		Whether you use mobile payment as the preferred payment method when purchasing seedlings, fertilizers and other agricultural materials
		Do you use your mobile phone for learning and education activities
		Do you use your mobile phone for entertainment such as games?

questionnaire: "Do you encounter any difficulties when using a 4G/5G phone?" "Do you communicate about important public affairs within the village through WeChat groups?" "Do you prefer the village committee to use WeChat or other online means to convey information?" "Does your household operate any products that are traded online?" "Do you use mobile as your preferred payment method when purchasing seeds, fertilizers, and other agricultural supplies?" "Do you use your phone for educational activities?" "Do you use your phone for entertainment activities such as games?" to measure farmers' digital application capabilities. Based on the above variables, the reliability and validity of digital capability were tested. The KMO value for digital capability was 0.685, indicating that the digital capability evaluation indicator system is suitable for factor analysis. Therefore, this study employed factor analysis to quantitatively evaluate farmers' digital capabilities, ultimately deriving a comprehensive digital capability index.

Control variables. In order to control the influence of other factors, with reference to related studies, this paper controls other characteristic variables affecting the sales income of agricultural products, mainly including the age, gender, education level of farmers, and family insurance participation.

Mechanism variables. Based on the previous analysis, the mechanism variables in this paper include agricultural labor productivity and green production behavior of farmers. Agricultural labor productivity is measured by average crop production, it is measured by the ratio of total crop production to agricultural labor. And green behavior refers to related research (Liu et al., 2020), focusing on whether farmers have reduced fertilizer application, reduced pesticide application, whether organic fertilizer is applied, whether pesticide packaging is recycled, whether straw is returned to the field, whether conservation tillage is applied, and whether water-saving irrigation is applied, and the number of adoption of the above production measures by farmers is summed up to measure green behavior (Table 2).

3.3 Data source

This paper is based on data from the 2020 China Rural Revitalisation Survey (CRRS), a dynamic tracking survey of rural villages conducted every 2 years, covering 10 provinces (autonomous regions) including Guangdong, Anhui, Shaanxi, Guizhou and Ningxia, and providing authoritative, representative and stable data. The survey adopts the methods of stratified sampling, isometric sampling and random sampling, taking into account the county-level per capita GDP, the economic development of townships and villages, and the rules of the village roster, etc., and the survey data cover 50 counties (cities and districts), 156 townships, 308 administrative villages, and 15,922 individual samples across the country. After removing the missing values and outliers of key variables, a total of 5,222 observations are retained in accordance with the research theme of this paper.

4 Results

4.1 Benchmark regression

Table 3 reports the benchmark regression results of digital capability on farmers' operating income. The results in column (1) of Table 3 reflect the direct impact of digital capability on farmers' operating income. The coefficient of the core explanatory variable, digital capability, is significantly positive, indicating that for every one-unit increase in digital capability, farmers' operating income increases by 0.2758 units. This suggests that as farmers' digital capabilities continue to improve, they can effectively promote the growth of farmers' operating income. From the results after controlling for other variables, the effect of digital capability on farmers' operating income remains significantly positive, confirming that the core conclusion of this study holds even when controlling for other factors.

4.2 Endogenous issues

Omitted Variable Analysis. Due to the impact of village characteristics on farmers' business income, there may be omitted variable issues in the baseline regression results. This endogeneity problem can be addressed by controlling for village characteristics. The regression results with village control variables are shown in column (1) of Table 4, where digital capability still has a significant positive effect on farmers' business income.

Instrumental Variable Method. Although factors such as education level that influence household business income have been controlled for, the characteristics of business income may still introduce other potential influencing factors in the model. To mitigate endogeneity issues, digital access conditions are selected as instrumental variables, with the proxy variable being "household computer ownership" in villages. This is mainly because computer ownership is closely related to household digital capabilities and does not directly affect household business income. Columns (2) and (3) of Table 4 report the regression results using the instrumental variable method, and the conclusions remain largely consistent with those discussed earlier.

4.3 Robustness check

To further verify the robustness of the results, this paper conducts robustness tests on the regression results by replacing explanatory variables and econometric models. First, factor 1 and factor 2 from factor analysis are used to re-measure farmers' digital capabilities, as shown in columns (1) and (2) of Table 5. The regression results indicate that digital capability still has a significant positive impact on farmers' operating income, demonstrating that the conclusions of the benchmark regression remain valid even after replacing the core explanatory variable measurement method. Second, since the dependent variable, farmers' operating income, is a continuous variable, this paper further selects quantile regression for robustness testing. Column (3) of Table 4 shows that even after replacing the econometric model, digital capability still has a significant positive impact on farmers' operating income, further confirming the robustness of the benchmark regression results. Finally, to exclude outliers among control variables, they are subjected to bilateral trimming at the 1% quantile before regression, as shown in column (4) of Table 5. Digital capability still has a significant positive impact on farmers' operating income, further confirming the robustness of the benchmark regression results.

4.4 Heterogeneity analysis

In order to deepen the understanding of the relationship between digital capability and farmers' operating income, this paper explores the heterogeneous influence of digital capability on farmers' operating income with different group characteristics and analyzes the heterogeneous influence of digital capability on farmers' operating income from the perspectives of education level and operation scale, respectively.

Heterogeneity of Farmers' Ages. The digital capabilities of farmers of different ages may vary, which could affect their household business income. Since the age of 60 is the critical point at which the physical strength of agricultural workers significantly declines (the World Health Organization (WHO) and most countries define 60 as the starting point of "old age"). This paper divides the entire sample into two groups: those under 60 years old and those over 60 years old, to conduct an age heterogeneity test. The estimation results are shown in columns (1) and (2) of Table 6. It can be seen that the positive impact of digital capability on household business income is mainly concentrated among those under 60 years old. This may be because this group of farmers has more progressive thinking and uses digital tools more frequently compared to the older group, thus enjoying greater digital dividends. Cognitive decline raises the expense of mastering digital technology for people 60 and older. This group is less likely to gain from the digital dividend because they also have a tendency to gradually distance themselves from intense agricultural production and have a lower demand for digital technologies.

Heterogeneity of Farming Scale. Agricultural scale helps to improve farmers' production efficiency and ensure operating profits. This paper measures the scale of farming operations using the area of arable land operated by households, dividing the sample into large-scale farmers and small farmers based on an operating area threshold of 6666.67 square meters. The regression results are shown in columns (3) and (4) of Table 6. The impact of digital capability on the operating income of small farmers is not significant, whereas it has a significant positive effect on the operating income of large-scale farmers. The possible reason lies in the fact that, for small-scale farmers, the limited size of their cultivated land results in higher unit costs for using data tools. Additionally, within the context of the platform economy, digital platforms often exclude small-scale farmers. Therefore, even if small-scale farmers possess high digital capabilities, they are

TABLE 2 Descriptive statistics of variables.

Variable name	Sample capacity	Mean	SD	Min	Max
Agricultural product sales revenue	5,222	9.5038	1.5353	3.6889	13.8169
Digital capabilities	5,222	3.9306	0.4458	2.9486	5.9881
Gender	5,222	0.5105	0.4999	0	1
Age	5,222	55.2551	12.0412	31	82
Educational attainment	5,222	3.1310	1.8142	1	8
Participation in agricultural insurance	5,222	0.3987	0.4897	0	1
Credit sales of products	5,222	0.1542	0.3611	0	1
Agricultural production efficiency	5,222	0.8995	0.1924	0	1
Green production behavior	5,222	1.5810	1.0974	0	6

Data source: Statistical data from the 2020 "Comprehensive Survey on Rural Revitalization in China."

TABLE 3 The impact of digital capabilities on agricultural product sales revenue.

Variable	Agricultural product sales revenue					
	(1)	(2)	(3)	(4)	(5)	(6)
Digital capabilities	0.2758***	0.2761***	0.2367***	0.2441***	0.2338***	0.2305***
	(5.4912)	(5.4977)	(4.6379)	(4.7761)	(4.5823)	(4.5533)
Gender		0.0305	0.0271	0.0310	0.0295	0.0297
		(0.7205)	(0.6391)	(0.7320)	(0.6989)	(0.7084)
Age			−0.0079***	−0.0080***	−0.0075***	−0.0071***
			(−4.4701)	(−4.4905)	(−4.2235)	(−4.0283)
Educational attainment				−0.0247**	−0.0246**	−0.0247**
				(−2.0667)	(−2.0702)	(−2.1101)
Participation in agricultural insurance					0.2585***	0.2587***
					(6.0383)	(6.1030)
Credit sales of products						0.5476***
						(10.1862)
Constant term	8.4199***	8.4031***	8.9972***	9.0453***	8.9566***	8.8625***
	(43.2011)	(42.8126)	(37.5863)	(37.5489)	(37.1632)	(37.2520)
Observed value	5,222	5,222	5,222	5,222	5,222	5,222
R^2	0.0064	0.0065	0.0102	0.0111	0.0178	0.0344

***, **, and * represent significance at the 1, 5, and 10% statistical levels, respectively; t-statistics are in parentheses.

TABLE 4 Results of endogeneity testing based on omitted variable analysis and instrumental variable methods.

Explained variable	Farmers' operating income		
	(1)	(2)	(3)
	Missing variable analysis	Stage I	Stage II
Digital capabilities	0.2750***		0.2054*
	(0.0505)		(0.1139)
Digital access conditions		0.4033***	
		(0.0120)	
Controlled variable	YES	YES	YES
Observed value	5,222	5,222	5,222
R^2	0.0566	0.2139	0.0344

***, **, and * represent significance at the 1, 5, and 10% statistical levels, respectively; parentheses are clustered robust standard errors.

TABLE 5 Robustness test.

Variable	(1)	(2)	(3)	(4)
	Replace explanatory variable		Replace the metering model	Remove outliers
Digital capabilities	0.1090***	0.0807***	0.2694***	0.2305***
	(4.7563)	(3.0339)	(4.2044)	(4.5533)
Controlled variable	YES	YES	YES	YES
Constant term	9.7421***	9.8582***	8.8317***	8.8625***
N	5,222	5,222	5,222	5,222
Adj. R^2	0.0343	0.0320		0.0344

***, **, and * represent significance at the 1, 5, and 10% statistical levels, respectively; t-statistics are in parentheses. The first and second columns of the table show the results of robustness tests for replacing the core explanatory variables, the third column shows the results of robustness tests for replacing the econometric model, and the fifth column shows the results after removing outliers.

constrained by the limitations of their operational scale and find it difficult to share the costs of technology. For large-scale farmers, however, who typically own contiguous farmland, the unit cost of using digital tools is lower. Additionally, with the support of digital platforms and green certification systems, their digital capabilities can enhance their resource integration capacity and technological adaptability, thereby achieving economies of scale and increasing their operational income.

Heterogeneity of Village Topography. There are significant differences in infrastructure construction and transportation accessibility among households in different terrain areas, which may lead to variations in household operating income due to digital capabilities. This paper divides the entire sample into plains, hills, and mountains for a heterogeneity test of topography, with estimation results shown in columns (5) to (7) of Table 6. It can be seen that at the 1% significance level, digital capability has a significant positive effect on the operating income of households in hill areas. At the 5% significance level, digital capability also has a significant positive effect on the operating income of households in plain areas, but its impact on the operating income of households in mountainous areas is not significant and fails to pass the significance test. The possible reasons are that in hill areas, plots are scattered but of moderate size, and the improvement in digital capability enables farmers to better utilize lightweight digital agricultural machinery, enhancing technological dividends. Even if plain areas have a rather well-developed digital infrastructure, the effects of digital capabilities on marginal income generation are somewhat modest. Yet, because of the plains' distinct topography, farmers can usually profit from the digital spillover effects through industrial clusters; mountainous regions are usually isolated, with dispersed terrain, small farmland, poor coverage of mobile communication infrastructure, expensive logistics, and limited technological adaptability. Because of this, digital premiums are frequently fully offset, meaning that digital capabilities have little effect on the operational income of farmers in mountainous areas.

4.5 Mechanism testing—mediation effects test

Logically speaking, the improvement of farmers' digital capabilities can effectively reduce the information asymmetry between supply and demand of agricultural products, so as to encourage farmers to participate more actively in agricultural product sales activities. Based on this, referring to Jiang's mediating effect research, this paper further identifies the mechanism by which digital capabilities promote the increase of farmers' operating income from two aspects: increasing agricultural production efficiency and encouraging farmers to practice green production.

Increasing agricultural production efficiency. In the current context of accelerating digital rural construction, efficiently utilizing digital tools is crucial for agricultural development. Enhancing digital capabilities can broaden farmers' access to information and explore more efficient production methods, thereby contributing to an increase in their operating income. To test whether digital capabilities can promote an increase in farmers' operating income through the mechanism of improving agricultural productivity, this paper uses labor crop yield to measure agricultural production efficiency. The regression results shown in Table 7 column (1) indicate that the regression coefficient for digital capability is 0.0195, which is significant at the 1% level. This suggests that digital capability drives improvements in agricultural productivity, highlighting its positive role in optimizing the allocation of agricultural resources. Improvements in agricultural production efficiency mean that more output can be generated per unit of input, directly increasing farmers' operating income. At the same time, improvements in agricultural production efficiency will reduce production costs due to economies of scale, further increasing farmers' income. Therefore, digital capability promotes an increase in farmers' operating income by enhancing agricultural productivity. Hypothesis 2a is verified.

Encouraging farmers to practice green production. Digital capabilities reduce the economic barriers and market frictions associated with green production practices, becoming a key lever for farmers to achieve "green income growth." Enhancing digital capabilities can effectively optimize agricultural production decisions, strengthen the application of digital technologies, minimize resource waste and pollution, lower agricultural production costs, and benefit from relevant policy incentives, thereby promoting an increase in farmers' operating income. To test whether digital capabilities can promote farmers' operating income growth through their role in encouraging green production, this paper measures agricultural green production using the sum of seven indicators of green agricultural production behavior. The regression results shown in Table 7 column (2) indicate that the regression coefficient for digital capabilities is 0.2149, which is significant at the 1% level, revealing the positive impact of digital capabilities on farmers' green production behavior from a green production perspective. The internalizing externalities theory states that green production lowers long-term production costs by reducing resource depletion and environmental damage. According to the notion of agricultural value chain appreciation, green production is frequently accompanied by the branding and standardization of green certification, which helps premium prices be paid for high-quality agricultural products and raises farmers' operating revenue. Therefore, digital capabilities estimate that green production promotes farmers' operating income growth. Hypothesis 2b is thus verified.

5 Discussion

The digital economy performs a significant function in the agricultural process as modernization of agriculture and rural areas continues to progress. The research that is now available primarily

TABLE 6 The effect of digital capabilities on farmers' operational income across various age groups, arming scale, and village topographies.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Older age-group	The younger group	Large-scale farmers	Small farmers	Plain	Hills	Mountain area
Digital capabilities	0.1624*	0.2456***	0.5135***	0.0384	0.1417**	0.5914***	0.0047
	(0.0891)	(0.0619)	(0.0605)	(0.0641)	(0.0680)	(0.0956)	(0.0977)
Controlled variable	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Group difference test	Pass through		Pass through				
Observed value	1,602	3,620	2,438	2,784	2,338	1,159	1,725
R^2	0.0269	0.0356	0.0605	0.0156	0.0234	0.1094	0.0258

***, **, and * represent significance at the 1, 5, and 10% statistical levels, respectively; parentheses are clustered robust standard errors. A test for age heterogeneity was performed after the complete sample was split into two groups: those under 60 and those above 60. The area of farmland owned by households was used to calculate farm size, and a threshold of 10 mu (about 1.65 acres) was used to separate the sample into large-scale and small-scale farmers. A test for topographical heterogeneity was carried out after the complete sample was separated into plains, hills, and mountains.

examines the influence of digital technology on agriculture from a macro perspective; quite rarely do these studies address how the digital capabilities of farmers affect agricultural product sales. The influence of the application capability of digital technology on farmers' income has only been discussed by a handful of academics. For instance, Fang et al. (2020) utilized a logistic regression model to conduct a quantitative investigation into the mechanism of the agricultural Internet with the goal of increasing farmers' income levels from three perspectives: farmers' characteristics, platform cognition, and society. The influence of digital skills on farmers' agricultural entrepreneurship and the mechanisms that underlie it were investigated by Cheng et al. (2024). In addition, the researchers confirmed the income-increasing effect of farmers' digital capabilities from the perspective of non-agricultural revenue.

Compared to previous studies, this paper contributes new insights. Theoretically speaking, this study cuts in from the perspective of farmers, carefully explores the impact of farmers' digital capabilities on agricultural product sales, and excavates the theoretical mechanism of farmers' digital capabilities affecting agricultural product sales. It not only enhances the study content of the analysis of the effect of digital village development policy assessment, but also improves the quantitative basis of the policy evaluation. Meanwhile, this article further defines the significance of digital capabilities in promoting agricultural product sales from two aspects: efficiency enhancement and green production practices, elaborating on the mechanism via which digital capabilities affect agricultural product sales. At the practical level, it first demonstrates the significance of digital capabilities in the development of digital villages and subsequently gives an accurate reference for optimizing the path of digital villages. Secondly, through heterogeneity analysis, the differences in digital capabilities between age, production scale and terrain are clarified; This not only provides empirical support for the formulation of regional differentiation policies, but also provides targeted guidance for the digitization of specific production processes.

6 Research limitations

By highlighting the under-studied mechanisms that link farmers' digital capability to sales performance and highlighting the influence of age, farming scale, and village topography differences on outcomes, this study adds significantly to our understanding of how digital capabilities can support agricultural product sales in rural China. However, it still has a number of limitations. First off, although this study shows how digital capabilities can impact sales of agricultural products by promoting green behavior and production efficiency, it does not investigate the factors that motivate digital participation. To make this series of studies more comprehensive, future study should examine the factors that influence digital involvement in greater detail. Second, the capacity to deduce causal correlations is restricted by the cross-sectional CRRS data utilized in this investigation. Future studies should investigate experimental techniques or longitudinal panel data to create time series in order to better validate the findings of this paper. Lastly, future study should focus on the dynamic nature of digital adoption across time and regional differences in digital infrastructure.

TABLE 7 The mediating effect of improved production efficiency and green quality enhancement on the impact of digital capabilities on agricultural product sales.

Variable	Agricultural production efficiency	Practice green production
	(1)	(2)
Digital capabilities	0.0195***	0.2149***
	(0.0059)	(0.0367)
Controlled variable	Controlled	Controlled
Observed value	5,222	5,222
R^2	0.0205	0.0246

***, **, and * represent significance at the 1, 5, and 10% statistical levels, respectively; the cluster standard error is in parentheses.

7 Conclusions and policy recommendations

7.1 Conclusion

This paper measures farmers' digital capability levels from three dimensions: digital access conditions, digital information acquisition capabilities, and digital application capabilities. Based on an analysis of how digital capabilities facilitate agricultural product sales, the paper adopts a micro-level perspective of farmers to elucidate improvements in agricultural production efficiency and green quality, systematically revealing the underlying mechanisms through which digital capabilities influence agricultural product sales. The study conducts empirical tests using micro-level farmer data to establish a empirical link between digital capabilities and agricultural product sales, addressing gaps in current research. The study's conclusions are as follows: First, farmers' proficiency with technology can greatly boost their revenue from the selling of agricultural products. An intrinsic driving factor for China's agricultural development is the encouragement of the creation of "digital villages," the further introduction of digital technology in rural regions, and the enhancement of farm households' digital capabilities. The conclusion is still valid following a number of robustness tests. Second, increasing farmers' digital capabilities can boost agricultural product sales in two ways: by increasing agricultural production efficiency and encouraging farmers to practice green production to raise the quality of their products, which will raise sales revenue. Third, the impact of farmers' digital skills on the sales of agricultural products is especially noticeable among young farmers, large-scale farmers, and farmers in hilly regions. These results point to a reality that merits our consideration. The challenge of marketing agricultural products is made worse by the growing wealth disparity between urban and rural communities and the growing issue of the countryside being hollowed out. Given the pressing need for "triple transformation" in rural areas and the ongoing promotion of the digital village construction project, the primary challenge facing agricultural groups at the moment is leveraging the digital economy's trend to boost revenue from the sale of agricultural products. The main topic here is whether or not expanding digital capabilities to alter the behavior of agricultural production and the way agricultural products are sold may boost agricultural sales revenue, and if so, how. In addition to being extremely valuable for the study of sustainable agricultural growth in China, the identification of these patterns has important implications for many other nations dealing with issues related to agricultural development.

7.2 Policy recommendations

The study makes the following suggestions in light of the aforementioned findings.

First and foremost, develop farmers' digital skills and fortify the rural digital infrastructure. First, the government should raise investment in digital rural development and support rural network construction. To provide complete 5G network coverage in administrative villages, relevant departments should take the initiative in collaborating with significant network base stations. Create and enhance a system for teaching farmers in digital skills, including free courses in rural areas on topics like big data analysis, IoT usage, and live streaming for e-commerce. To guarantee that farmers have access to a quality platform for enhancing their digital skills, assign instructors in digital skills to small groups within villages at the same time. Second, digital platforms that are appropriate for rural development should be aggressively developed by agricultural technology enterprises. By creating intelligent platforms for the production and sale of agricultural products, they may accomplish traceability throughout the entire agricultural industry chain and break down barriers to communication between farmers and customers through dialect voice interaction technologies. Lastly, in order to achieve transparency in seed and fertilizer prices and make comparisons easier for farmers, rural cooperatives should actively respond to pertinent policies by digitizing farmers' land parcels and creating internal agricultural input procurement platforms with the assistance of agricultural technology companies.

Secondly, adapt solutions to regional circumstances to develop unique programs for enhancing digital capacity. First, the government can provide incentives like commission waivers for youth using digital platforms and encourage youth to return to rural areas for development. Establish digital innovation hubs for new farmers, actively support preferential policies for them, and elevate their standing. Work together to provide pertinent courses with vocational colleges. For "new farmers," agricultural technology companies can offer internships to improve their practical abilities. Second, put in place favorable interest rate policies for larger farmers in order to promote precision farming systems and encourage them to adopt digital instruments for operations. At the same time, actively teach small-scale farmers how to use digital applications and create digital tools that are specific to their production requirements. Lastly, the development of offline operating systems for agricultural production, the training of skilled personnel for system operation, the promotion of specialty agriculture, and the use of blockchain traceability and AI-based quality inspection to improve the reputation of agricultural products from mountainous regions are all crucial given the difficulties in achieving complete network coverage in these areas. Digital agricultural industrial parks can be developed in plain locations with fertile soil to create smart farms and draw talent, thus enhancing farmers' digital skills. Targeted training on the usage of slope drones and micro-weather stations can be provided to farmers in hilly regions with complicated terrain. In the leisure agricultural industry, a VR terraced field tourist system can also be created to boost farmers' earnings.

Thirdly, enhancing digital productivity and accelerating the green transformation of agriculture. On the one hand, improve rural network coverage, establish agricultural big data centers and village-level digital service stations, and set up specialized departments responsible for the use of agricultural digital equipment. Encourage the use of agricultural technology, actively develop and recruit talent to work in agriculture, and work toward intelligent agricultural production throughout time. To lower farmers' production costs and increase agricultural production efficiency, the government should aggressively support intelligent agricultural equipment and tools, provide farmers with planting decision-making network platforms, and precisely provide pertinent agricultural production recommendations. On the other hand, the government should create a green traceability platform for agricultural products, improve the agricultural green certification system, create an ecological compensation mechanism, include agricultural carbon emissions in the performance evaluation criteria for rural officials, use digital technology to develop green agricultural products, and establish a "green production" support system. To reduce agricultural non-point source pollution, agricultural technology businesses should employ network technology to match farmers with accurate orders and use algorithms to give farmers precise planting and fertilizing plans. To better understand consumer demand for green agricultural products, promote agricultural green transformation, and increase sales of agricultural products, cooperatives should set up digital production records, consistently purchase green agricultural inputs, and organize members to conduct live-streamed sales.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WX: Methodology, Writing – original draft, Writing – review & editing.

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Conflict of interest

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

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1657139/full#supplementary-material

References

Arham, M. A., Fadhli, A., and Dai, S. I. (2020). Does agricultural performance contribute to rural poverty reduction in Indonesia? *JEJAK* 13:69–83. doi: 10.15294/jejak.v13i1.20178

Bawden, D. (2001). Information and digital literacies: a review of concepts. *J. Doc.* 57:218–259. doi: 10.1108/EUM0000000007083

Brandtzæg, P. B., Heim, J., and Karahasanović, A. (2011). Understanding the new digital divide—a typology of internet users in Europe. *Int. J. Hum.-Comput. Stud.* 69, 123–138. doi: 10.1016/j.ijhcs.2010.11.004

Chen, Y., Hu, S., and Wu, H. (2023). The digital economy, green technology innovation, and agricultural green total factor productivity. *Agriculture* 13:19-61. doi: 10.3390/agriculture13101961

Chen, Q., Lin, H., and Lu, Z. (2014). Can village democracy increase happiness? A survey based on 1,800 farm households in 120 poor villages in central and western China. *China Econ. Q.* 13, 723–744. doi: 10.13821/j.cnki.ceq.2014.02.005

Cheng, C., Gao, Q., Ju, K., and Ma, Y. (2024). How digital skills affect farmers' agricultural entrepreneurship? An explanation from factor availability. *J. Innov. Knowl.* 9, 1–13. doi: 10.1016/j.jik.2024.100477

Clark, C., and Gorski, P. (2002). Multicultural education and the digital divide: focus on socioeconomic class background. *Multicult. Perspect.* 4:25–36. doi: 10.1207/s15327892mcp0403_6

Evans, O. (2018). Digital agriculture: mobile phones, internet and agricultural development in Africa. *Actual Probl. Econ.* 7, 205–206. Available online at: https://econpapers.repec.org/paper/pramprapa/90359.htm

Fang, Y., Fan, Y., Yu, D., Shen, J., Jiang, W., and Yu, D. (2020). Impact of farmers' benefits linking stability on cloud farm platform of company to farmer model. *Agric. Econ.* 66, 424–433. doi: 10.17221/68/2020-AGRICECON

Fu, C., Sun, X., Guo, M., and Yu, C. (2024). Can digital inclusive finance facilitate productive investment in rural households? - an empirical study based on the China household finance survey. *Financ. Res. Lett.* 61:105034. doi: 10.1016/j.frl.2024.105034

Gong, S., Sun, Z., Wang, B., and Yu, Z. (2024). Could digital literacy contribute to the improvement of green production efficiency in agriculture? *SAGE Open* 14:21582440241232789. doi: 10.1177/21582440241232789

Guo, X., Wang, L., Meng, X., Dong, X., and Gu, L. (2023). The impact of digital inclusive finance on farmers' income level: evidence from China's major grain production regions. *Financ. Res. Lett.* 58:104531. doi: 10.1016/j.frl.2023.104531

Iost Filho, F. H., Heldens, W. B., Kong, Z., and de Lange, E. S. (2020). Drones: innovative Technology for use in precision Pest management. *J. Econ. Entomol.* 113, 1–25. doi: 10.1093/jee/toz268

Jensen, R. (2007). The digital provide: information (technology), market performance, and welfare in the south Indian fisheries sector. *Q. J. Econ.* 122, 879–924. doi: 10.1162/qjec.122.3.879

Kelikume, I. (2021). Digital financial inclusion, informal economy and poverty reduction in Africa. *J. Enterprising Commun. People Places Glob. Econ.* 15:626–640. doi: 10.1108/JEC-06-2020-0124

Leroux, N., Wortman, M. S., and Mathias, E. D. (2001). Dominant factors impacting the development of business-to-business (B2B) e-commerce in agriculture. *Int. Food Agribus. Manag. Rev.* 4, 205–218. doi: 10.1016/S1096-7508(01)00075-1

Li, H., and Jiang, H. (2023). Effect of the digital economy on farmers' household income: county-level panel data for Jilin Province, China. *Sustainability* 15:44-50. doi: 10.3390/su15054450

Li, D., Kojima, D., Wu, L., and Ando, M. (2024). Impact of rural households' digital ability on their production efficiency in China. *Agribusiness* 40, 139–160. doi: 10.1002/agr.21836

Liu, S., Jin, Y., and Zheng, F. (2024). Did product certification and e-commerce benefit agricultural producers in China? *Food Policy* 127, 102688–102611. doi: 10.1016/j.foodpol.2024.102688

Liu, Y., Sun, D., Wang, H., Wang, X., Yu, G., and Zhao, X. (2020). An evaluation of China's agricultural green production: 1978–2017. *J. Clean. Prod.* 243:118483. doi: 10.1016/j.jclepro.2019.118483

Long, H., Zhang, Y., and Tu, S. (2019). Rural vitalization in China: a perspective of land consolidation. *J. Geogr. Sci.* 29, 517–530. doi: 10.1007/s11442-019-1599-9

Ma, W., Grafton, R. Q., and Renwick, A. (2020). Smartphone use and income growth in rural China: empirical results and policy implications. *Electron. Commer. Res.* 20, 713–736. doi: 10.1007/s10660-018-9323-x

Marshall, A., Dezuanni, M., Burgess, J., Thomas, J., and Wilson, C. K. (2020). Australian farmers left behind in the digital economy – insights from the Australian digital inclusion index. *J. Rural. Stud.* 80, 195–210. doi: 10.1016/j.jrurstud.2020.09.001

Njuguna, E., Daum, T., Birner, R., and Mburu, J. (2025). Silicon Savannah and smallholder farming: how can digitalization contribute to sustainable agricultural transformation in Africa? *Agric. Syst.* 222:104180. doi: 10.1016/j.agsy.2024.104180

Obare, G. O. (2013). Strategic positioning of marketplaces and learning institutions as digital village centres for rural empowerment and development in Bondo District. *Int. J. Bus. Soc. Res.* 3, 58–73. doi: 10.18533/ijbsr.v3i9.274

Parra-López, C., Ben Abdallah, S., Garcia-Garcia, G., Hassoun, A., Trollman, H., Jagtap, S., et al. (2025). Digital technologies for water use and management in agriculture: recent applications and future outlook. *Agric. Water Manag.* 309:109347. doi: 10.1016/j.agwat.2025.109347

Polloni-Silva, E., da Costa, N., Moralles, H. F., and Neto, M. S. (2021). Does financial inclusion diminish poverty and inequality? A panel data analysis for Latin American countries. *Soc. Indic. Res.* 158, 889–925. doi: 10.1007/s11205-021-02730-7

Reuschke, D., and Mason, C. (2022). The engagement of home-based businesses in the digital economy. *Futures* 135:102542. doi: 10.1016/j.futures.2020.102542

Rijswijk, K., Klerkx, L., and Turner, J. A. (2019). Digitalisation in the New Zealand agricultural knowledge and innovation system: initial understandings and emerging organisational responses to digital agriculture. *NJAS-Wagen. J. Life Sci.* 90:100313, –91. doi: 10.1016/j.njas.2019.100313

Shen, Z., Wang, S., Boussemart, J.-P., and Hao, Y. (2022). Digital transition and green growth in Chinese agriculture. *Technol. Forecast. Soc. Change* 181:121742. doi: 10.1016/j.techfore.2022.121742

Shimamoto, D., Yamada, H., and Gummert, M. (2015). Mobile phones and market information: evidence from rural Cambodia. *Food Policy* 57, 135–141. doi: 10.1016/j.foodpol.2015.10.005

Siaw, A., Jiang, Y., Twumasi, M. A., and Agbenyo, W. (2020). The impact of internet use on income: the case of rural Ghana. *Sustainability* 12:3255. doi: 10.3390/su12083255

Tambo, J. A., and Wünscher, T. (2017). Farmer-led innovations and rural household welfare: evidence from Ghana. *J. Rural. Stud.* 55, 263–274. doi: 10.1016/j.jrurstud.2017.08.018

Ting, J. (2022). Mediating and moderating effects in empirical studies of causal inference. *China Indust. Econ.*, 100–120. doi: 10.19581/j.cnki.ciejournal.2022.05.005

Wang, Y., Weng, F., and Huo, X. (2023). Can digital finance promote professional farmers' income growth in China?—an examination based on the perspective of income structure. *Agriculture* 13:1103. doi: 10.3390/agriculture13051103

Wijerathna-Yapa, A., and Pathirana, R. (2022). Sustainable agro-food systems for addressing climate change and food security. *Agriculture* 12:1554. doi: 10.3390/agriculture12101554

Xie, L., Luo, B., and Zhong, W. (2021). How are smallholder farmers involved in digital agriculture in developing countries: a case study from China. *Land* 10:245. doi: 10.3390/land10030245

Yuan, L., and Luo, C. (2025). E-commerce, Employment Transformation, and Income Growth for Farmers. *Nankai Economic Research* 22–44. doi: 10.14116/j.nkes.2025.04.002

Zhang, X., and Fan, D. (2023). Can agricultural digital transformation help farmers increase income? An empirical study based on thousands of farmers in Hubei Province. *Environ. Dev. Sustain.* 26, 14405–14431. doi: 10.1007/s10668-023-03200-5

Zhang, H., Ma, W., Li, J., and Yang, W. (2023). Can citrus farmers earn more from selling online? *Econ. Anal. Policy* 80, 1549–1560. doi: 10.1016/j.eap.2023.10.026

Zheng, S., Yu, L., and Fu, H. (2023). Has rural e-commerce increased potato farmers' income? Evidence from the potato home of China. *Potato Res.* 67, 15–35. doi: 10.1007/s11540-023-09614-y