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Low-carbon effects of farmers' digital economy participation: further discussing digital equality

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Introduction: Under the urgent need to deal with climate change and achieve the dual-carbon goal, integrating the digital economy and traditional agriculture has become an important starting point for promoting the low-carbon agricultural transformation. In the context of the digital economy, it will be more practical to pay attention to the main role of micro-farmers in low-carbon agricultural development.

Methods: This paper uses farmer survey data from 10 provinces in China, including Guangdong, Zhejiang, Shandong, and Heilongjiang, to study the impact and mechanism of digital economy participation on farmers' low-carbon production performance.

Results: Digital economy participation can significantly improve farmers' low-carbon production performance. Farmers' low-carbon production willingness and low-carbon production behavior are important ways for digital economy participation to exert low-carbon effects. Farmers with rural elite status and outworking who participate in the digital economy will actively improve their low-carbon production performance.

Discussion: Digital economic inequality will impact the low-carbon effect of farmers' digital economy participation. This effect is more obvious for farmers with older age and lower education levels.

KEYWORDS

digital economy participation, farmer carbon productivity, digital inequality, low-carbon agricultural production performance, "dual carbon" goal

1 Introduction

In 2020, China's General Secretary Xi Jinping proposed at the 75th United Nations General Assembly the strategic goal of striving to peak carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060 (i.e., the dual-carbon goal). Agriculture is one of the major sources of greenhouse gas emissions (Zhao et al., 2022). Agricultural carbon emission reduction is important for addressing climate change and realizing the dual-carbon goal (Song et al., 2023). For this reason, Chinese authorities have issued a series of policies to control carbon emissions from agricultural production to encourage low-carbon agricultural production, such as *The 14th Five-Year National Green Agricultural Development Plan*, The No. 1 Central Document of 2023 and 2024. Farmers are the most important participants in low-carbon agricultural development (Qi and Jiang, 2013). Paying attention to the main role of farmers in agricultural response to climate change, strengthening farmers' low-carbon production behavior, and improving farmers' low-carbon production performance from a micro perspective is of great significance to achieving agricultural carbon emission reduction (Chen and Kong, 2022). However, farmers face the three major dilemmas of unwillingness, inability and inability to carry out low-carbon production, which will result in the problem of low agricultural low-carbon production performance (Yang and Xu, 2015; Chen and Jiang, 2017; Kragt et al., 2017). Enhancing farmers' enthusiasm and efficiency in low-carbon production has become the key to solidly promoting agricultural carbon emission reduction and steadily realizing the dual-carbon goal.

With the rapid development of the digital economy, the agricultural industry has also experienced digital transformation (Ma S. Z. et al., 2022). The digital economy takes reducing information asymmetry as its logical starting point. Reshaping the capabilities of agricultural operators and changing agricultural production methods deeply penetrates the agricultural and rural economy and continuously empowers farmers with low-carbon production behaviors, creating new possibilities and opportunities to achieve low-carbon agricultural development (Liu, 2019; Wen and Chen, 2020). Therefore, we should correctly understand and explore the issue of farmers' low-carbon production performance under the dual background of the booming digital economy and global climate change. Does farmers' digital economy participation impact their low-carbon production performance? What is the extent of the impact? What is the mechanism of action? These questions need to be further studied.

2 Literature review

There are many studies evaluating the development of the digital economy and exploring its impact. Most studies evaluate the digital economy from a macro perspective by building module indicators, which generally include indicators in infrastructure digitization, industry digitization, etc. (Nicholson, 2020; Zhao et al., 2020; Liu, 2022). There are few studies on micro-family surveys with the theme of digital economy and measure them (Huang et al., 2023). Micro-level research mainly uses Internet usage and Internet embedding to measure the degree of digital economy penetration (Mao and Zeng, 2017; Rui and Fang, 2018; Yao et al., 2020; Song et al., 2021; Jin et al., 2024), measures the Chinese resident digitalization index from the two dimensions of digital technology access and digital skills use (Huang et al., 2023), or describes farmers' digital economy participant from three aspects: digital production, digital supply and marketing, and digital finance (Peng et al., 2022; Wang et al., 2024). Digital economy development will drive farmers' income growth (Qi et al., 2021), consumption upgrades (Wang and Wang, 2021), and an improvement in the quality of employment and entrepreneurship (Zhao et al., 2023). Although it would be more comprehensive to examine digital economy development from a macro perspective, factors such as age, gender, and region will lead to micro-individuals' inability to participate in digital economic services. That is, they will not be able to obtain the dividends of the digital economy (Zhang and Wang, 2023) and even aggravate digital inequality in rural areas (Sen, 2020). However, transformative digitalization's potential may be proclaimed in the existing literature. Attaining such goals partly depends on the beneficiaries' ability to take advantage of emerging digital services (Philip and Williams, 2019). Therefore, it is necessary to emphasize the importance of participation in the development of the digital economy, and it will be crucial to explore the impact of digital economy from a micro level.

Some existing studies emphasize the agricultural carbon emission reduction effect brought about by embedding digital information technology into the production process of micro-farmers. These studies have found that digital economy participation, embodied in digital finance, Internet use, digital technology promotion, etc., will encourage farmers to adopt low-carbon production behavior (Abdulai et al., 2023; Ma Q. H. et al., 2022; Weng, 2023; Zhang Y. et al., 2023). This is because digital economy participation has an absolute advantage in breaking the dual constraints of resources and information and achieving optimal resource allocation (Mao et al., 2023; Zhu et al., 2019; Harou et al., 2022). This unique advantage can improve human, social, natural, and financial capital (Dzanku et al., 2022; Purcell et al., 2022; Deng et al., 2022). Specifically, Internet use can encourage farmers to proactively adopt straw return technology (Huang and Nie, 2023). Digital technology will prompt grain farmers to reduce the use of chemical fertilizers by 3.45 to 5.85% (Jiang et al., 2021; Zhang H. L. et al., 2023); ICT use significantly promotes farmers' adoption of quality and safety production behaviors (Sun and Zou, 2024). E-commerce participation can significantly increase the adoption of green production technologies by kiwifruit growers, and technology cognition has a positive intermediary effect (Ma, 2023). Moreover, e-commerce participation will also positively impact farmers' cultivated land quality protection behavior, which is beneficial for farmers in reducing fertilization (Zhang et al., 2022). It is worth noting that farmers need to ensure the sustainable development of the agricultural economy by adopting low-carbon production behaviors and reducing agricultural carbon emissions. Therefore, Cheng (2021) believes that the construction of the digital economy is conducive to improving agricultural total factor productivity, but he only discusses it from a theoretical level (Guo et al., 2023). Although other studies explore the impact of the digital economy and agricultural total factor productivity from an empirical perspective, they mostly use meso-level enterprise or macro-provincial data (Cheng, 2021; Coderoni and Vanino, 2022; Xu et al., 2022). Thus, this does not reflect the individual effects of low-carbon agricultural development during the agricultural digital transformation stage.

To summarize, the present work thus goes beyond the existing literature in three main ways. Firstly, it goes deep into the micro level to analyze. In this paper, the 3,833 farmers used as samples come from 308 administrative villages in 150 townships in 50 counties in 10 provinces in China. It will be a comprehensive and scientific study of the wide heterogeneity of farmers' production practices, agricultural, natural resources and digital economy development. Secondly, it emphasizes participation in the digital economy and measures its degree. At the micro level, it is limited to measure the digital economy from a single perspective, such as Internet use or participation in rural e-commerce, making it difficult to truly reflect the enabling effect of the digital economy. Based on the core connotation of the digital economy, this paper is guided by the industrial chain theory, from agricultural production, agricultural production marketing and rural financial services three dimensions to build a comprehensive evaluation index system about digital economy participation. Thirdly, it not only estimates farmer carbon productivity at the micro level but also appraises the impact of digital economy participation on farmer carbon productivity. The latter is one of the major contributions made by the present paper. While paying attention to the agricultural economy growth, the externalities brought by agricultural production, that is, environmental factors, must be considered (Zhang Z. et al., 2023). Therefore, the carbon emissions farmers produce are included in the analysis framework of economic growth as an environmental factor, and farmer carbon productivity is put forward. It is worth noting that this paper examines the relationship between digital economy participation and farmer carbon productivity at the micro level. It may allow the eventual emergence of a win-win situation in which a higher degree of digital economy participation is associated with higher development of low-carbon agricultural products. To the best of the authors' knowledge, this is the first attempt to carry out such an assessment at the micro level for the agricultural sector.

3 Theoretical analysis

3.1 Analysis of the impact of digital economy participation on farmers' low-carbon production performance

According to the industry chain theory, it is known that production, logistics, sales, financial services and other production and business activities together constitute an organic system of value creation for market players. Rural digital economy development depends on digital technology embedded in the whole agricultural industry chain links and promotes its transformation, upgrading and deep integration. Among them, digital agriculture, as the core of digital production, is the driving force behind the transformation of traditional agriculture, the stimulation of digital productivity, and the continuation of the blood for the rural digital economy. Digital supply and marketing characterized by smart logistics and network sales is the support for integrating and optimizing information, logistics and capital flows, accurate and efficient matching of various agricultural production factors and supply and demand of agricultural products, and providing the skeleton for the orderly operation of the rural digital economy. Digital finance provides an efficient and convenient financial service guarantee for digital production, supply and marketing. Digital economy participation embedded in agricultural production, supply and marketing, and financial services impact farmers' low-carbon production performance by reducing information mismatch as a logical starting point. It is mainly characterized by the factor allocation effect, supply and demand matching effect, and financial inclusion effect. The specific theoretical analysis framework is shown in Figure 1.

In terms of the factor allocation effect of digital economic participation, digital economic participation provides farmers with timely access to the information they need about agricultural production by changing how they used to access information in the past. This makes factor allocation more flexible and scientific, such as orderly promoting land transfer, labor transfer and outsourcing production links. Under the consensual factor allocation, the change of factor input preference and the adoption of low-carbon agricultural production technology are conducive to improving farmers' low-carbon production performance. Regarding the supply and demand matching effect of digital economic participation, digital economic participation solves the problem of farmers' information asymmetry by filling the gaps in market information and sales channels. Increased demand for green agricultural products will stimulate farmers' low-carbon production. In the context of easy access to transaction information and smooth sales channels, accurate matching of market demand will help improve farmers' low-carbon production performance. In terms of the financial inclusion effect of digital economy participation, digital economic participation enhances the penetration and affordability of rural finance by alleviating the financing constraints in farmers' low-carbon production. Using the advantages of the availability and diversity of digital financial services to provide credit support for farmers' low-carbon production is conducive to improving farmers' low-carbon production performance. Based on this, this paper proposes the following hypothesis:

> H_1: Digital economy participation positively impacts farmers' low-carbon production performance.
>
> H_{1a}: Digital production participation positively impacts farmers' low-carbon production performance.

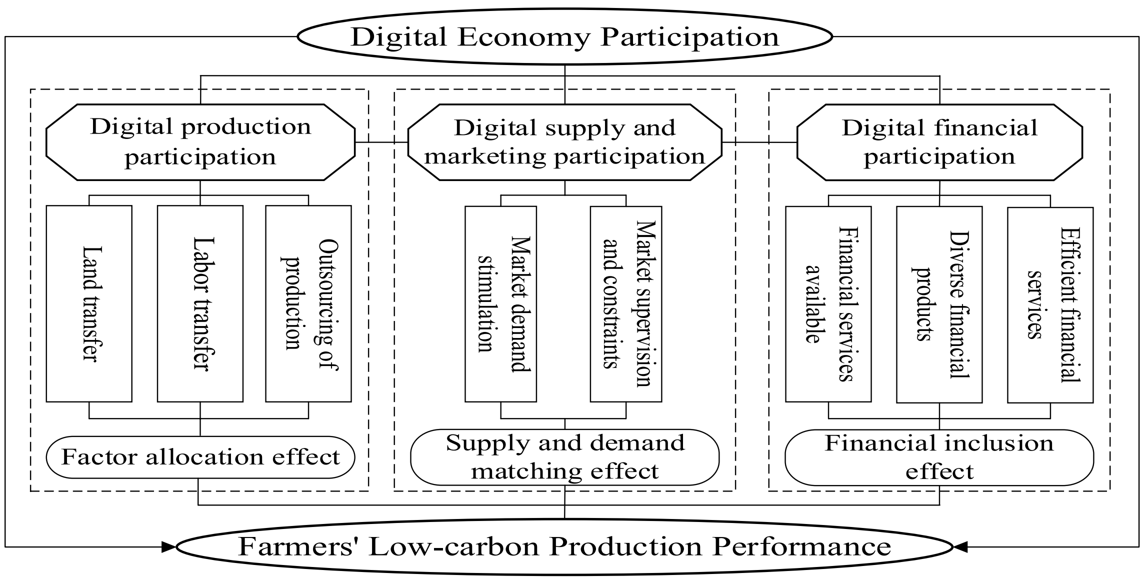

FIGURE 1
Theoretical analysis framework of the impact of digital economy participation on farmers' low-carbon production performance.

> H_{1b}: Digital supply and marketing participation positively impacts farmers' low-carbon production performance.
>
> H_{1c}: Digital finance participation positively impacts farmers' low-carbon production performance.

3.2 Analysis of the impact path of digital economy participation on farmers' low-carbon production performance

Digital economy participation impacts farmers' low-carbon production performance by changing farmers' low-carbon production willingness and behavior. Firstly, digital economy participation can make it easier for farmers to obtain environmental, market, technical and policy information about low-carbon agricultural production, which is more conducive to farmers' awareness of the benefits and importance of low-carbon agricultural production in the whole agricultural system (Kuang and Xie, 2011). The higher the willingness of farmers to engage in low-carbon agricultural production, the more conducive it is to improving farmers' low-carbon production performance (Luo, 2023). Secondly, digital economy participants can break the information barriers between farmers and consumers, speed up the logistics of green agricultural products, and broaden communication channels in the agricultural product market, thus driving farmers to engage in low-carbon agricultural production (Mei, 2016). The farmers' low-carbon production behavior significantly positively impacts their low-carbon production performance (Zhang and Luo, 2024). Thirdly, the theory of planned behavior believes that behavioral intention is the direct factor that determines actual behavior (Wu et al., 2020). Farmers' low-carbon production willingness can impact farmers' low-carbon production performance by impacting their low-carbon production behavior. Accordingly, this paper puts forward the following hypotheses:

> H_2: Digital economy participation improves farmers' low-carbon production performance by enhancing their low-carbon production willingness.
>
> H_3: Digital economy participation enhances farmers' low-carbon production performance by improving their low-carbon production behavior.

4 Research design

4.1 Data source

The China Rural Revitalization Survey (CRRS) database used in this paper comes from the Rural Development Institute of the Chinese Academy of Social Sciences. The survey team conducted a questionnaire survey on 3,833 farmers in 50 counties, 150 towns, and 308 administrative villages in 10 provinces, including Guangdong, Zhejiang, Shandong, and Heilongjiang in China from August to September 2020. The survey data is divided into three parts: individuals, families, and villages, including personal characteristics and work status of the surveyed subjects, income and expenditure of the surveyed families, agricultural production status, and organizational status and social and economic undertakings of the surveyed villages. Therefore, this database can provide scientific and reasonable data to support this study.

4.2 Variable selection and measurement

4.2.1 Dependent variable: farmers' low-carbon production performance of farmers

Carbon productivity is an important indicator for measuring low-carbon economic development. Compared with the total carbon emissions, it has the dual goals of economic growth and carbon emission reduction, which is more in line with the reality of China's carbon emissions relative reduction stage (Ajzen, 1985). Farmers' carbon productivity can indicate farmers' low-carbon production performance. Carbon productivity is widely used in academia and includes total-factor carbon productivity and single-factor carbon productivity. International conventions generally reflect the emission reduction responsibility arrangement under the single-factor framework (Pan et al., 2010), directly reflecting the degree of achievement of the dual goals of reducing carbon emissions and promoting economic growth. Moreover, Wang and Gao (2018) believe that the improvement of total-factor carbon productivity does not mean that the carbon emission reduction situation will definitely be improved, and the inefficient part without separation of factors may also lead to errors in the measured carbon productivity (Sun et al., 2012). Therefore, this paper uses single-factor carbon productivity to measure low-carbon production performance. Referring to the research of Kaya and Yokobori (1997), farmers' carbon productivity is defined as the ratio of farmers' agricultural income to their agricultural production carbon emissions (Wang and Gao, 2018). Farmers' agricultural income refers to the total net income of their planting and breeding industries. Agricultural production carbon emissions are calculated from two aspects: planting and breeding (Kaya and Yokobori, 1997). Specifically, planting carbon emissions mainly include agricultural material inputs (fertilizers, pesticides, agricultural films, agricultural irrigation and machinery) and farmland soil use. Carbon emissions from animal husbandry mainly include methane emissions from animal intestinal fermentation and methane and nitrous oxide emissions from animal manure management. Drawing on the research results of Tian and Yin (2022), the agricultural carbon emission calculation formula is constructed: $C = \sum C_i = \sum T_i \times \delta_i$ (Huang et al., 2024), where C represents the total carbon emissions of farmers' agricultural production; C_i represents the carbon emissions of each carbon source; T_i represents the use of each carbon emission source; δ_i represents the carbon emission coefficient of each carbon source. The carbon emission coefficients of planting and animal husbandry are shown in Tables 1, 2, respectively.

4.2.2 Treatment variable: digital economy participation

The digital economy participation in this paper includes participatory behavior in three aspects: digital production, supply and marketing, and finance. The following questions are used to measure farmers' digital economy participation (as shown in Table 3). If farmers participate in at least one of the three digital production activities, digital supply and marketing, and digital finance, the sample is identified as digital economy participation, represented by variable

TABLE 1 Carbon emission source and carbon emission factors of animal husbandry.

Region	Cow	Non-cow	Sheep	Goat	Pig	Poultry	Horse	Donkey/mule	Camel
Methane emission factors for fecal management (kg CH_4/head)									
North China	7.46	2.82	0.25	0.17	3.12	0.01	1.09	0.60	1.28
Northeast	2.23	1.02	0.25	0.16	1.12	0.01	1.09	0.60	1.28
East China	8.33	3.31	0.26	0.28	5.08	0.02	1.64	0.90	1.92
Central South	8.45	4.72	0.34	0.31	5.85	0.02	1.64	0.90	1.92
Southwest	6.51	3.21	0.48	0.53	4.18	0.02	1.64	0.90	1.92
Northwest	5.93	1.86	0.28	0.32	1.38	0.01	1.09	0.60	1.28
Nitrous oxide emission factors for fecal management (kg N_2O/head)									
North China	1.846	0.794	0.093	0.093	0.227	0.007	0.330	0.188	0.330
Northeast	1.096	0.913	0.057	0.057	0.266	0.007	0.330	0.188	0.330
East China	2.065	0.846	0.113	0.113	0.175	0.007	0.330	0.188	0.330
Central South	1.710	0.805	0.106	0.106	0.157	0.007	0.330	0.188	0.330
Southwest	1.884	0.691	0.064	0.064	0.159	0.007	0.330	0.188	0.330
Northwest	1.447	0.545	0.074	0.074	0.195	0.007	0.330	0.188	0.330
Methane emission factor from the intestinal fermentation (kg CH_4/head)									
Nationwide	85.0	71	8.6	8.9	1.5	-	18	10	46

Provincial Greenhouse Gas Inventory Compilation Guide and 2006 IPCC Guidelines for National Greenhouse Gas Inventory.

TABLE 2 Carbon emission source and carbon emission factors of the planting industry.

Agricultural material inputs		Farmland soil utilization	
Agricultural material	Carbon emission coefficient	Crop	Carbon emission coefficient (kg·hm^{-2})
Fertilizer	0.896 kg·kg^{-1}	Paddy	210 (CH_4)、0.240 (N_2O)
Pesticide	4.934 kg·kg^{-1}	Soybean	0.770 (N_2O)
Agricultural film	5.180 kg·kg^{-1}	Corn	2.532 (N_2O)
Agricultural irrigation	266.480 kg·hm^{-2}	Vegetables	4.210 (N_2O)
Agricultural machinery	$P \times 16.470$ kg·hm^{-2} + $W \times 0.180$ kg·kW^{-1}		

The carbon emission coefficients of fertilizers and pesticides come from the Oak Ridge National Laboratory (ORNL) in the United States. The carbon emission coefficients of agricultural films come from the Institute of Resource, Ecosystem, and Environment of Agriculture (IREEA) of Nanjing Agricultural University. The carbon emission coefficients of agricultural machinery come from the IPCC (P represents agricultural planting area, and W represents the total power of agricultural machinery). The carbon emission coefficients of farmland soil utilization of various carbon sources and agricultural irrigation refer to the research results of Liu and Liu (2022) and Tian and Yin (2022).

0 or 1. In addition, referring to the research of Zhu (2024), the entropy method is used to measure the degree of digital economy participation (Liu and Liu, 2022). Statistics show that the proportion of farmers' participation in digital production, digital supply and marketing, and digital finance in the sample is 27.86, 6.10, and 92.30%, respectively.

4.2.3 Mediator variable: farmers' low-carbon production willingness and farmers' low-carbon production behavior

This paper uses questions such as "Whether domestic sewage is scientifically treated?" "Whether domestic waste is classified and disposed of?" and "Whether there are harmless sanitary toilets?" to measure farmers' daily low-carbon life and to characterize whether farmers have low-carbon production willingness. This paper uses questions such as "Whether to rotate farming?," "Whether to fallow?," "Whether to treat crop straw scientifically?" and "Whether to dispose of pesticide packaging scientifically?" are used to characterize farmers' low-carbon production behavior. The entropy method is used to calculate the farmers' low-carbon production willingness index and farmers' low-carbon production behavior index. Statistics show that the proportion of farmers with low-carbon production willingness and low-carbon production behavior in the sample is 45.16 and 45.19%, respectively.

4.2.4 Control variable

This paper selects corresponding control variables from three aspects: individual farmer (household head) characteristics, farmer agricultural production, and fiscal support effects. However, due to space limitations, this paper does not explore the differentiated generation logic of farmer digital production, digital supply and marketing, and digital finance participation. That is, no distinction is made in the selection of control variables. The definitions, assignments, and descriptive statistics of the above variables are shown in Table 4.

TABLE 3 Farmers' digital economy participation measurement system.

	Participation category	Variable meaning	Assignment
Digital economy participation (DEP)	Digital production participation (DPP)	Do you obtain agricultural production information through WeChat public accounts, professional apps or agriculture-related websites?	Yes = 1 No = 0
		Are digital technologies such as artificial intelligence, the IoT, or drones used?	
	Digital supply and marketing participation (DSMP)	Have you sold agricultural products through e-commerce platforms like Douyin/Kuaishou, Jingdong/Taobao, etc.?	
		Have you received e-commerce training and guidance services to achieve online sales of agricultural products?	
	Digital finance participation (DFP)	Have you used Internet financial platforms like WeChat or Alipay to pay for agricultural production materials?	
		Have you used Internet financial platforms like WeChat or Alipay to purchase financial products?	
		Have you used Internet financial platforms like WeChat or Alipay for credit loans?	

4.3 Model settings

The empirical goal of this paper is to test the impact of digital economy participation on farmers' carbon productivity. To this purpose, this paper uses OLS to perform regression estimation on the multivariate linear model. The model is constructed as follows:

$$CP_i = \alpha_1 + \beta_1 DEP_i + \gamma_1 X_i + \varepsilon_i \tag{1}$$

In the Equation 1, CP_i represents farmers' carbon productivity; DEP_i represents farmers' digital economy participation; X_i represents other control variables impacting farmers' carbon productivity, including individual, family, and environmental characteristics; α_1 represents a constant term; β_1 and γ_1 represent parameters to be estimated; ε_i represents a random disturbance term.

There may be two types of endogeneity problems in this paper, namely, the omitted variable problem and the self-selection bias problem. In response to the omitted variable problem, this paper attempts to find a suitable instrumental variable to control the endogeneity of the model. Drawing on the practice of Fu and Huang (2018), the spherical distance from the village to Hangzhou is selected as the instrumental variable for farmers' digital economy participation (Zhu, 2024). Generally, the closer the spherical distance from the village to Hangzhou, the more sensitive the farmers are to the digital economy and the greater the possibility of participating in the digital economy, which conforms to the principle of relevance. Besides, the spherical distance from the village to Hangzhou has no direct connection with the farmers' digital economy participation, which conforms to the principle of exogeneity. The traditional instrumental variable method is generally implemented through the two-stage least squares method (2SLS).

Regarding the self-selection bias problem, that is, whether to participate in the digital economy is a self-selection behavior of farmers. The behavior can be impacted by various factors such as individual farmer characteristics, resource endowment, etc., which may simultaneously impact farmers' carbon productivity. This leads to systematic differences, causing bias in the impact of digital economy participation on farmers' carbon productivity. The propensity score matching method (PSM) reduces the systematic differences of samples by matching resampling to make the observed data close to random experiments. It not only can insulate the model estimates from selection bias due to sample self-selection but also can avoid the problem of extrapolation bias due to model misspecification (Fu and Huang, 2018). Based on the counterfactual analysis idea of PSM, the samples can be divided into a digital economy participation group and a digital economy non-participation group. The average treatment effect of digital economic participation is defined as:

$$ATT = E\left(C_{1i} \middle| D_i = 1\right) - E\left(C_{0i} \middle| D_i = 1\right) = E\left(C_{1i} - C_{0i} \middle| D_i = 1\right) \tag{2}$$

In the Equation 2, C_{1i} and C_{0i} represent the carbon productivity of the same farmer i in the two cases of participating in the digital economy and not participating in the digital economy. The research sample is limited to the digital economy participation group ($D_i = 1$), and the difference between farmers participating in the digital economy and not participating in the digital economy is calculated. However, in reality, it is impossible to observe the carbon productivity of each farmer in both states simultaneously. Therefore, PSM can be used to match farmers who do not participate in the digital economy in the digital economy participation group with a similar sample and find the alternative value of $E(C_{0i} \mid D_i = 1)$. To ensure the robustness of the regression results, this paper will use three different matching methods for matching simultaneously. The low-carbon effect of digital economy participation can be expressed as:

$$\begin{aligned} ATT &= E\left\{E\left[C_{1i} - C_{0i} \middle| D_i = 1, P\left(X_i\right)\right]\right\} \\ &= E\left\{E\left[C_{1i} \middle| D_i = 1, P\left(X_i\right)\right] - E\left[C_{0i} \middle| D_i = 0, P\left(X_i\right)\right] = 1\right\} \end{aligned} \tag{3}$$

In the Equation 3, $P(X_i)$ represents the propensity score, which refers to the conditional probability of farmer i participating in the digital economy under the conditions specified by specific variables, and is calculated as the Equation 4:

$$P\left(X\right) = pr\left(D_i = 1 \middle| X_i\right) = \exp\left(\beta X_i\right) / \left[1 + \exp\left(\beta X_i\right)\right] \tag{4}$$

According to the theoretical analysis in the previous paper, digital economy participation mainly impacts farmers' low-carbon production performance through two paths: enhancing farmers' low-carbon production willingness and improving farmers' low-carbon production behaviors. Therefore, this paper draws on the

TABLE 4 Variable definitions and descriptive statistics.

Variable category	Variable name	Variable definition	Mean	Standard deviation
Dependent variable	Farmers' carbon productivity (CP)	Farmers' agricultural income/Agricultural production carbon emissions (%)	12.3195	225.0804
Treatment variable	Digital economy participation (DEF)	Whether there is digital production, supply and marketing, and financial participation: Yes = 1; No = 0	0.9498	0.2184
		Digital economy participation level	0.0458	0.0702
Mediator variable	Farmers' low-carbon production willingness (FPW)	Farmers' willingness to participate in low-carbon production	0.4426	0.3461
	Farmers' low-carbon production behavior (FPB)	Farmers' adoption of low-carbon production behavior	0.1916	0.2074
Control variable	Age (AGE)	Household head age (years)	54.8734	11.6550
	Education level (EDU)	Household head's education level: No schooling = 1; Preschool education = 2; Primary school = 3; Junior high school = 4; High school (technical secondary school) = 5; University (college) = 6; University and above = 7	3.6054	1.0699
	Rural elite identity (VC)	Whether the household head has served as a village cadre: Yes = 1; No = 0	0.1532	0.3602
	Disaster rate (DR)	Crop-affected area/Crop sown area (%)	12.7171	30.6537
	Agricultural industrial structure (AIC)	Animal husbandry income/Total income (%)	0.1642	0.3699
	Agricultural development foundation (ADE)	Agricultural income (yuan)	20602.33	76974.29
	Agricultural financial support (AFS)	National planting, animal husbandry, production materials, land transfer, ecological compensation/returning farmland to forest and other policy subsidies (yuan)	3244.169	13142.96
	Rural financial support (RFS)	Farmers' loan channels: Formal financial institutions = 1; Informal financial institutions = 0	0.1519	0.3589

research of Tian and Yin (2022) and takes farmers' low-carbon production willingness and farmers' low-carbon production behaviors as mediation variables (Ke et al., 2022). Following the general idea of a causal stepwise regression test, the model is set as Equations 5–7:

$$CP_i = \alpha_1 + \beta_1 DEP_i + \gamma_1 X_i + \varepsilon_i \tag{5}$$

$$M_i = \alpha_2 + \beta_2 DEP_i + \gamma_2 X_i + \rho_i \tag{6}$$

$$CP_i = \alpha_3 + \beta_3 DEP_i + \lambda_3 M_i + \gamma_3 X_i + \tau_i \tag{7}$$

Where M_i represents the mediating variable, and the meanings of other variables are the same as before. It is important to ensure the reliability of the mediation effect. This paper uses the Zmediation statistic test method to test the validity of the mediation effect model and uses the Sobel mediation factor test method to test it.

5 Results analysis

5.1 Benchmark regression results

In order to empirically test the impact of digital economy participation on farmers' carbon productivity, regression analysis is performed using OLS and fixed effects model (FE) based on the model setting, and robust standard errors are used to avoid possible heteroskedasticity problems. The regression results are shown in Table 5. Columns 1–3 are the empirical results of OLS regression analysis, and columns 4–6 are the empirical results of adding village fixed effects. The comparison reveals that the fixed effects model's empirical results remain robust. Accordingly, this paper uses the fixed effects model as the benchmark regression result to conduct the analysis. The results show that the digital economy participation variable is significant, and the coefficient is positive. That is, farmers' digital economy participation can significantly improve their low-carbon production performance. Furthermore, digital production, supply, and marketing participation also positively impact farmers' carbon productivity, among which digital supply and marketing participation have a greater promoting effect. This is because the supply-marketing matching effect stimulates farmers' low-carbon production more directly, which will have a greater impact on production performance. However, the proportion of digital supply and marketing participation in digital economy participation is relatively low, so there may be a problem that the low-carbon effects of farmers' digital economy participation cannot be sustained. Digital finance participation has no significant impact on farmers' low-carbon production performance. Relevant research believes that digital inclusive finance can increase green total factor productivity, and its impact will be greater when the economy and industrial chain develop better. However, rural financial development is low, and the demand for innovation in the agricultural industry chain is not high, so it is not easy to attract advanced production factors to create favorable conditions for improving farmer household productivity (Li, 2024; Zhang and Wang, 2024). In summary, hypotheses H_1, H_{1a} and H_{1b} are confirmed.

5.2 Discussion on endogeneity

5.2.1 Instrumental variable method

Although the fixed effects model used in the previous benchmark regression can greatly control the endogeneity problem caused by omitted variables, there may still be individual unobservable characteristics. Therefore, to ensure the reliability of the empirical results, this paper further uses the instrumental variable method to solve the endogeneity problem in the model and selects the spherical distance (DIS) from the village to Hangzhou City as the instrumental variable for farmers' digital economy participation. As shown in Table 6, the F statistic in the first stage is 7.3734, rejecting the weak instrumental variable hypothesis. At the same time, the Sargan test p-value is 1, which means that the null hypothesis that the instrumental variable is exogenous cannot be rejected. The second-stage regression results show that digital economy participation still significantly promotes farmers' carbon productivity.

5.2.2 Propensity score matching method

This paper uses the propensity score matching method (PSM) to solve the self-selection bias problem that may exist in the benchmark regression model. In order to ensure that the matching results of the propensity score matching method are accurate and reasonable, this paper first conducts a balance test before analyzing the impact of digital economy participation on farmers' carbon productivity. The nearest neighbor matching method is used for data matching. When the standardized deviation after sample matching is less than 20%, it means that the propensity score matching method has successfully obtained the matching result (Wang et al., 2022). According to Table 7, the standardized deviation after sample matching has been greatly reduced and is controlled within 20%, indicating that the propensity score matching method reduces the sample bias. That is, the matching result is effective.

In addition, in this paper, the fitted value of the conditional probability p_i of digital economic participation of farmer i, i.e., the propensity score, is calculated based on the estimation results of the decision equation for farmers' digital economy participation. This paper further draws a kernel density map to more intuitively test the common support domain after sample matching. As shown in Figure 2, after matching, there is a large overlap in the propensity scores between the experimental group that participates in the digital economy and the control group that does not participate in the digital economy, and most of the observed values are in the common value range. This once again confirms that the matching results are effective.

Based on the balance test and the common support domain test results, it is clear that the matched digital economy participation group and the digital economy non-participation group are balanced in terms of characteristics, and the matching effect is good. Therefore, the average treatment effect of farmers' digital economy participation on their low-carbon production performance is calculated using the nearest neighbor matching method. As shown in Table 8, except for the ATT effect value of digital financial participation, which is not significant, the ATT effect values of the other variables are significant ($p < 0.05$). The ATT effect values are 12.7809, 12.4868, and 12.3885, respectively. It shows that digital economy participation, production participation, and supply and marketing participation can significantly promote farmers' carbon productivity. Among them, farmers' digital economy participation can improve their low-carbon production performance by 12.78%. This conclusion is consistent with the previous conclusion obtained using the instrumental variable method to solve the endogeneity problem. To summarize, hypotheses H_1, H_{1a} and H_{1b} are confirmed.

5.3 Robustness test

This paper uses four methods to conduct robustness tests: weight adjustment, replacement of explained variables, replacement test method, and replacement of sample data to verify the impact of digital economy participation on farmers' carbon productivity.

5.3.1 Weight adjustment

By modifying the matching method to conduct a robustness test, the average treatment effect results of farmers' digital economy participation on their low-carbon production performance are shown in Table 9. The average treatment effect of farmers' digital economy participation is slightly different under the four matching methods: local linear, spline, radius, and kernel matching. Among them, except for the average treatment effect result of the spline matching method, which is significant at the 5% level, the average treatment effect results of the other matching methods are all significant at the 1% level. Overall, the average treatment effect has a mean value of 13.5311. This shows that compared with farmers who do not participate in the digital economy, farmers who participate in the digital economy will be more likely to achieve low-carbon agricultural development. This further verifies the robustness of the previous results.

5.3.2 Replacement test method

The endogenous switching regression model can solve the endogeneity problem caused by sample selection by fitting counterfactual inference to compare the impact of projects and policies (Wang et al., 2022). Therefore, this paper uses the endogenous switching model for the robustness test. As shown in Table 10, the ATT effect value obtained using the endogenous conversion model is 13.2350, consistent with the result obtained using propensity score matching. The two models can successfully capture the effect well when the predictive power of the outcome models is high (Araar, 2015). However, since the propensity score matching method only corrects the selective bias of observable variables, it will underestimate the low-carbon effect of farmers' digital economy participation to a certain extent (Leng and Zhu, 2018).

5.3.3 Replacing treatment variable

The degree of farmers' digital economy participation measured by the entropy method is used to measure it again, and the empirical test is conducted again. The results are shown in Column 1 in Table 11. The regression results show that digital economy participation has a significant positive impact on farmers' carbon productivity; that is, the previous regression results are robust.

TABLE 5 Benchmark regression results of digital economy participation on farmers' carbon productivity.

Variable	Farmer carbon productivity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DEP	0.0546** (0.0081)				0.0455*** (0.0083)			
DPP		0.0152*** (0.0049)				0.0115** (0.0050)		
DSMP			0.0193*** (0.0029)				0.0179*** (0.0030)	
DFP				0.0031 (0.0077)				0.0032 (0.0080)
AGE	0.0002** (0.0001)	0.0002** (0.0001)	0.0002** (0.0001)	0.0002** (0.0001)	0.0002** (0.0001)	0.0003*** (0.0001)	0.0002** (0.0001)	0.0003*** (0.0001)
EDU	0.0004 (0.0006)	0.0002 (0.0006)	0.0003 (0.0005)	0.0001 (0.0006)	0.0006 (0.0006)	0.0005 (0.0006)	0.0006 (0.0006)	0.0004 (0.0006)
VC	−0.0020* (0.0016)	−0.0024 (0.0016)	−0.0018 (0.0016)	−0.0026* (0.0015)	−0.0026 (0.0016)	−0.0029* (0.0016)	−0.0023 (0.0016)	−0.0030* (0.0016)
DR	−1.58e-06 (0.0000)	−4.06e-06 (0.0000)	−4.20e-07 (0.0000)	3.98e-06 (0.0000)	−3.47e-06 (0.0000)	−1.49e-07 (0.0000)	−2.54e-06 (0.0000)	5.35e-07 (0.0000)
AIC	−0.0176*** (0.0015)	−0.0173*** (0.0015)	−0.0177*** (0.0015)	−0.0174*** (0.0015)	−0.0175*** (0.0017)	−0.0175*** (0.0017)	−0.0176*** (0.0017)	−0.0176*** (0.0017)
ADE	0.5720** (0.0024)	0.5719** (0.0024)	0.5721** (0.0024)	0.5720** (0.0024)	0.5736** (0.0024)	0.5737** (0.0024)	0.5739** (0.0024)	0.5736** (0.0024)
AFS	−0.0005** (0.0002)	−0.0004** (0.0002)	−0.0005** (0.0002)	−0.0004** (0.0002)	−0.0004** (0.0002)	−0.0004** (0.0002)	−0.0004** (0.0002)	−0.0004** (0.0002)
RFS	−0.0063*** (0.0016)	−0.0073*** (0.0016)	−0.0061*** (0.0016)	−0.0074*** (0.0016)	−0.0067*** (0.0016)	−0.0075*** (0.0016)	−0.0064*** (0.0016)	−0.0076*** (0.0016)
Constant	1.0124*** (0.0335)	1.0112*** (0.0336)	1.0087*** (0.0335)	1.0100*** (0.0337)	0.9811*** (0.0343)	0.9789*** (0.0344)	0.9747*** (0.0343)	0.9769*** (0.0344)
Village fixed effect	Uncontrolled	Uncontrolled	Uncontrolled	Uncontrolled	Controlled	Controlled	Controlled	Controlled
R^2	0.9373	0.9367	0.9373	0.9365	0.9397	0.9393	0.9389	0.9392
N	3,806	3,806	3,806	3,806	3,806	3,806	3,806	3,806

***, **, and * are significant at 1, 5, and 10%, respectively. The robust standard error is indicated in parentheses. Same as below.

5.3.4 Replacing sample data

Although the China Rural Revitalization Survey (CRRS) data used in this paper covers nearly 4,000 farmers in ten provinces, the data was collected earlier. Therefore, the same theoretical framework and analytical methods are used to test the impact of digital economy participation on farmers' carbon productivity based on micro-survey data from Heilongjiang Province from July to September 2024 to help prove the robustness of the research results. As shown in Column 2 of Table 11, the regression results still show that digital economy participation has a significant positive impact on farmers' carbon productivity, thus clarifying the applicability of the conclusions obtained in this paper in the new era.

TABLE 6 Regression results of instrumental variable method.

Variable	Phase 1: digital economy participation	Phase 2: farmers' carbon productivity
DEP		0.1164***(0.0355)
DIS	0.0103***(0.0038)	
Control variable	Controlled	Controlled
Village fixed effect	Controlled	Controlled
R^2	0.9100	0.9392
F value	7.3734	
Sargan statistics		0.1695
N	3,806	3,806

5.4 Analysis of mediation effect

The above studies show that farmers' digital economy participation positively impacts their low-carbon production performance, but how they impact the improvement of their low-carbon production performance remains to be further verified. According to the previous analysis, farmers' digital economy participation mainly impacts their low-carbon production performance through two paths: enhancing

TABLE 7 PSM balance test.

Variable	Before and after matching	Mean value		Standardized deviation rate (%)	Standardized deviation reduction (%)	T value	*p* value
		Participating digital economy farmers	Non-participating digital economy farmers				
AGE	Before matching	54.7680	56.0310	−9.4	36.2	−4.19	0.000
	After matching	54.8270	55.7540	−6.9		−1.07	0.284
EDU	Before matching	3.6089	3.5393	6.1	51.8	0.88	0.381
	After matching	3.6133	3.6468	−2.9		−1.29	0.198
VC	Before matching	0.1559	0.1361	5.6	−15.9	2.35	0.019
	After matching	0.1544	0.1309	6.7		0.88	0.380
DR	Before matching	11.2110	11.2850	−21.3	69.7	−1.83	0.068
	After matching	11.2160	11.1940	6.4		0.55	0.583
AIC	Before matching	0.1695	0.0631	33.9	93	3.88	0.000
	After matching	0.1687	0.1761	−2.4		−0.87	0.382
ADE	Before matching	13.8300	13.8170	8.2	5.7	13.81	0.000
	After matching	13.8270	13.8140	7.8		0.76	0.448
AFS	Before matching	6.5485	6.4459	2.5	15.3	1.60	0.109
	After matching	6.5490	6.4622	2.1		0.95	0.340
RFS	Before matching	0.1508	0.1728	−6.0	73.1	−0.83	0.409
	After matching	0.1468	0.1409	1.6		0.71	0.478

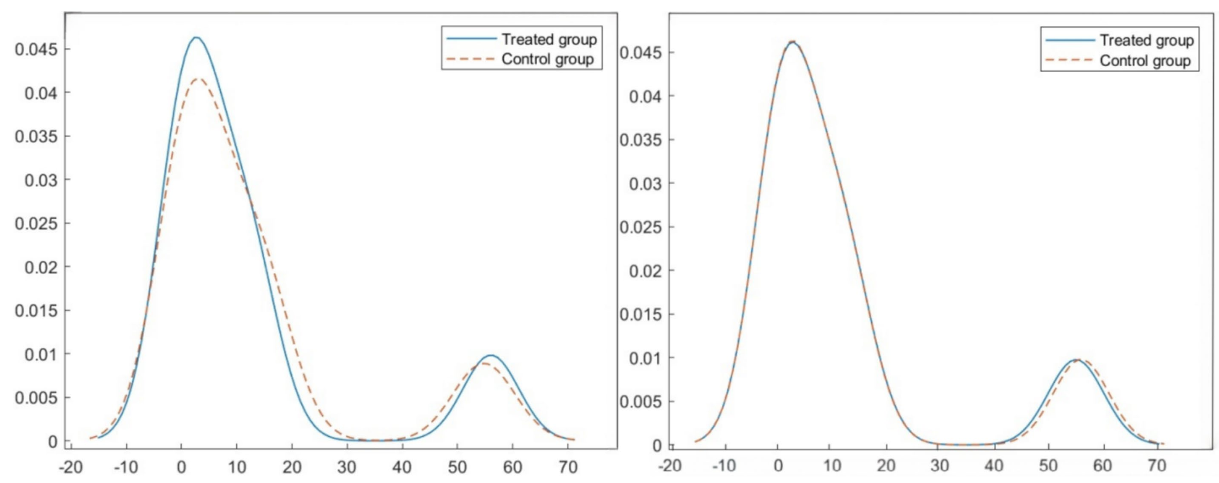

FIGURE 2
Kernel density distribution map before and after matching.

farmers' low-carbon production willingness and improving farmers' low-carbon production behaviors. This paper draws on the mediation effect test steps summarized by Wen and Ye (2014) and uses the matching samples after the previous PSM to test whether there is a mediation effect in the above two paths (Wen and Ye, 2014).

As shown in the estimation results in Columns 1 and 4 of Table 12, farmers' digital economy participation significantly positively impacts their low-carbon production performance, with an estimated coefficient of 0.0493. Columns 2 and 5 take farmers' low-carbon production willingness and farmers' low-carbon production behavior as the explained variables, respectively, and farmers' digital economy participation as the explanatory variable. Their estimated coefficients are both significantly positive. It shows that in the context of the digital economy, on the one hand, farmers can obtain more information about agricultural low-carbon development through digital technology to encourage farmers to increase their awareness of low-carbon production. On the other hand, digital technology can reduce various economic costs, such as search costs, copying costs,

TABLE 8 Mean treatment effect of digital economy participation impacting farmers' carbon productivity.

Variable	Experimental group	Control group	ATT	T value	*p* value
Digital economy participation (DEP)	15.1796	2.3988	12.7809	3.65	0.005
Digital production participation (DPP)	20.1503	7.6635	12.4868	2.33	0.021
Digital supply and marketing participation (DSMP)	13.1690	0.7805	12.3885	3.05	0.003
Digital finance participation (DFP)	−2.1352	9.5035	−11.8187	−0.59	0.415

and tracking costs for farmers in the process of low-carbon production, and it greatly encourages farmers to try out low-carbon agriculture. In Columns 3 and 6, the estimated coefficients of farmers' digital economy participation and their low-carbon production willingness and behavior are both significantly positive. Comparing the estimation results in Column 1 or Column 4, the marginal effect of farmers' digital economy participation has decreased, that is, from 0.0493 to 0.0489 and 0.0488, respectively. It shows that farmers' low-carbon production willingness and low-carbon production behavior are important ways for their digital economic participation to exert low-carbon effects. Judging from the impact coefficient, the mediation effects of farmers' low-carbon production willingness and low-carbon production behavior accounted for 8.69 and 35.27%, respectively. This means that approximately 8.69 and 35.27% of the low-carbon effects of farmers' digital economy participation are exerted through the mediating role of farmers' low-carbon production willingness and farmers' low-carbon production behavior. Thus, hypotheses H_2 and H_3 are verified.

5.5 Heterogeneity analysis

Given the differences in the foundation and conditions for the digital economy development in different villages and the capacity and resource endowment of different groups to participate in the digital economy, this paper further explores the impact of group heterogeneity of digital economy participation on farmers' carbon productivity. On the one hand, rural elite identity can impact farmers' social preferences, expectations, beliefs, and internal norms through identity labels and thus impact their behavioral decisions. This paper divides the farmer sample by whether they have served as a village cadre. The estimated results are shown in Table 13. Farmers with rural elite identity will actively improve their low-carbon production performance by participating in the digital economy, and farmers' low-carbon production willingness and farmers' low-carbon production behavior play a mediating role. This shows that rural elite groups can continuously enhance their low-carbon environmental awareness in the process of participating in the digital economy or give full play to their advantages in political resources, economic resources, and social relations to improve resource allocation efficiency. Ultimately, it is conducive to enhancing farmers' carbon productivity (Su et al., 2024). On the other hand, the flow of village labor is an important factor impacting the development of the rural digital economy. This paper divides the sample according to whether the farmers go out to work to test the heterogeneity of the impact of digital economy participation on farmers' carbon productivity under different village labor mobility conditions. The estimated results are shown in Table 13. Farmers who go out to work will greatly increase their willingness to produce low-carbon products after participating in the digital economy. That is the more labor mobility in the village, the higher the village's information accessibility and the stronger the mobility of resource elements, which is more conducive to introducing new concepts and technologies. It will help achieve the goal of low-carbon agricultural development (Fu and Huang, 2018).

6 Discussion

The conclusion drawn in this paper finds that digital economy participation will increase farmers' carbon productivity, but the premise of this effect is that these farmers have the conditions and opportunities to participate in the digital economy. If digital inequality exists, it will significantly impact individuals and families, exacerbating social exclusion and social stratification, especially in rural areas (Lefkofridi, 2014), where the likelihood of digital inequality is higher (Gladkova and Ragnedda, 2020). Digital inequality can lead to farmers losing certain rights or capabilities, thereby further exacerbating the inequality in farmers' income distribution and social welfare (Van Deursen Deursen et al., 2015). Therefore, this paper will next explore the impact of digital inequality on the low-carbon effects of farmers' participation in the digital economy.

In early concepts, digital inequality was considered the state of individual socioeconomic inequality caused by differences in Internet access and usage levels (Dimaggio, 2004). Subsequent studies have concluded from the absolute exclusion of access to digital media to differences in economic and social benefits obtained through skillful and informed usage of digital technology (Van Dijk, 2012). Digital inequality is not only reflected in differences in access to equipment or usage skills, but also involves the complex relationship between online resource allocation and offline social stratification (Van Dijk, 2005; Ragnedda, 2018). The appropriation of the technology depends on different kinds of access, and its basis rests on the motivation to use the technology. Therefore, in addition to evaluating digital inequality from digital access and information acquisition, some scholars have also articulated digital inequality in dimensions such as learning development and recreational interaction (Zhang and Zou, 2024). However, in the UK, the average broadband speed in rural areas was less than 10 Mbps, compared with 40 Mbps in urban areas (Ofcom, 2017), and in Lithuania, the same urban/rural divide exists, with users in the main cities being able to access services with speeds up to 100 Mbps, but less than 10% of those in the country districts being able to do so (RaskInterneta, 2017). Thus, the digital inequality in rural areas is more about digital access and access to information. This paper will obtain digital inequality by asking farmers questions such as "What Internet devices does your family have?," "How is the Internet condition at home?" "How timely do you want to obtain the information you focus on through your mobile phone or the Internet?" "Do you think the information obtained through the Internet can

TABLE 9 Mean treatment effects for other matching methods.

Matching method	Experimental group	Control group	ATT	T value	P value
Radius matching method	15.1796	1.8674	13.3122	3.89	0.001
Local linear matching method	15.1796	1.6485	13.5311	3.87	0.001
Kernel matching method	15.1796	1.3701	13.8095	4.08	0.001
Spline matching method	-	-	13.4716	3.72	0.002

In the radius matching method, the radius is selected as 0.001. The matching bandwidth is taken as the default value in the local linear and kernel matching methods. The ATT and t values of the spline matching method are obtained by iterating 500 times using the Bootstrap Method.

TABLE 10 Average treatment effects of digital economy participation impacting farmers' carbon productivity based on the endogenous switching regression model.

Group category	Decision-making stage		Treatment effect
	Participation in the digital economy	No participation in the digital economy	
Digital economy participation group	11.0284***(0.5077)	−1.2066***(0.1468)	13.2350***(0.5196)
Digital economy non-participation group	−1.3747***(0.1680)	−10.5664***(0.1834)	9.1917***(0.4365)

TABLE 11 Robustness test for the impact of digital economy participation on farmers' carbon productivity.

Variable	Farmer carbon productivity	
	(1)	(2)
DEP	0.0871*** (0.0263)	0.1377* (0.0812)
Control variable	Controlled	Controlled
Village fixed effect	Controlled	Controlled
R^2	0.9603	0.6374
N	3,806	364

meet daily needs such as production and life?" and "If there are daily needs, can you get relevant information at any time through your mobile phone or the Internet?" and conduct empirical tests based on this. The model containing the interaction term of digital economy participation and digital inequality is constructed as follows:

$$CP_i = \alpha_4 + \beta_4 DEP_i + \theta_4 DP_i + \delta_4 DEP_i \times DP_i + \gamma_4 X_i + \nu_i \tag{8}$$

In the Equation 8, DP_i represents digital inequality, and the meanings of other variables are the same as before. If δ_4 is significantly positive, it indicates a complementary effect. If δ_4 is significantly negative, it indicates a substitution effect.

On the one hand, differences in education level are the main factor leading to digital inequality (Goldfarb and Prince, 2008; Vicente and López, 2011). Referring to Wang (2024), the education level of farmers is divided into a low human capital group (below high school) and a high human capital group (high school and above). On the other hand, according to Lee et al. (2011), farmers aged 50 years and above are divided into the high age group, and farmers aged below 50 years are divided into the low age group. According to the empirical results in Table 14, digital economic inequality among farmers will impact the low-carbon effect of farmers' digital economy participation, especially for farmers with high age and low education. This is because more educated rural youth are able to use digital technologies to promote agricultural innovation in terms of agricultural technology choices (such as low-carbon technologies). However, most less educated farmers are unable to effectively use digital technologies due to their limited education level, perceived needs, and infrastructure, and are more inclined to choose solutions with lower technological content (Warren et al., 2000). This conclusion is consistent with the existing research results. Therefore, to fully play the low-carbon effect of farmers' digital economy participation, we must first solve the problems of farmers' digital access and information acquisition and focus on farmers with high age and low education.

7 Conclusion and policy implications

This paper uses survey data of farmers in 10 provinces in China, including Guangdong, Zhejiang, Shandong, and Heilongjiang, to empirically test the impact and mechanism of digital economy participation on farmers' low-carbon production performance. This paper shows that digital economy participation can significantly promote the improvement of farmers' low-carbon production performance, and digital production participation and digital supply and marketing participation will also have a positive impact on farmers' low-carbon production performance, among which digital supply and marketing participation has a greater impact on farmers' low-carbon production performance. Farmers' low-carbon production willingness and behavior are important ways to exert the low-carbon effects of farmers' digital economy participation. The participation of farmers with rural elite status in the digital economy will actively improve their low-carbon production performance, and farmers' low-carbon production willingness and low-carbon production behavior play a mediation effect. After participating in the digital economy, migrant farmers will greatly increase their willingness to produce low-carbon products and thus improve their performance. This paper further finds that digital economic inequality will impact the low-carbon effect of farmers' digital economy participation, especially for farmers with older ages and lower education levels.

TABLE 12 The result of the mechanism analysis.

Variable	Farmers' low-carbon production willingness			Farmers' low-carbon production behavior		
	(1)	(2)	(3)	(4)	(5)	(6)
DEP	0.0493*** (0.0088)	0.2679*** (0.0777)	0.0489*** (0.0088)	0.0493*** (0.0088)	0.2846*** (0.0846)	0.0488*** (0.0088)
FPW			0.0160* (0.0090)			
FPB						0.0611*** (0.0113)
AGE	0.0003*** (0.0001)	−0.0009* (0.0005)	0.0002*** (0.0000)	0.0003*** (0.0001)	−0.0004 (0.0005)	0.0002*** (0.0000)
EDU	0.0001 (0.0006)	−0.0006 (0.0054)	0.0005 (0.0006)	0.0001 (0.0006)	0.0270*** (0.0058)	0.0007 (0.0006)
VC	−0.0028* (0.0017)	0.0083 (0.0150)	−0.0022 (0.0016)	−0.0028* (0.0017)	0.0313* (0.0163)	−0.0026 (0.0017)
DR	−3.74e-06 (0.0000)	−0.0003* (0.0002)	−2.52e-06 (0.0000)	−3.74e-06 (0.0000)	−0.0011*** (0.0002)	9.17e-06 (0.0000)
AIC	−0.0189*** (0.0018)	−0.0357** (0.0160)	−0.0191*** (0.0016)	−0.0189*** (0.0018)	−0.0812*** (0.0160)	−0.0185*** (0.0018)
ADE	0.6159*** (0.0025)	0.0094 (0.0224)	0.6142*** (0.0025)	0.6159*** (0.0025)	0.0048 (0.0251)	0.6142*** (0.0025)
AFS	−0.0004* (0.0002)	−0.0001 (0.0020)	−0.0005*** (0.0002)	−0.0004* (0.0002)	−0.0144*** (0.0019)	−0.0003* (0.0002)
RFS	−0.0072*** (0.0017)	0.0191 (0.0152)	−0.0067*** (0.0017)	−0.0072*** (0.0017)	−0.0161 (0.0164)	−0.0069*** (0.0016)
Constant	1.150*** (0.1070)	0.7838** (0.3197)	0.4292*** (0.0354)	1.150*** (0.1070)	0.7887** (0.3605)	0.4315*** (0.0353)
R^2	0.9417	0.3079	0.9441	0.9417	0.5630	0.9398

TABLE 13 Heterogeneity regression results.

Variable	Non-rural elite identity group					Rural elite identity group				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DEP	−0.0008 (0.0054)	0.2004 (0.1610)	−0.0486 (0.2395)	0.0016 (0.0014)	−0.0008 (0.0054)	0.0633*** (0.0097)	0.3054*** (0.0973)	0.1981* (0.1204)	0.0629*** (0.0097)	0.0620*** (0.0097)
FPW				−0.0011 (0.0054)					0.0132* (0.0080)	
FPB					0.0003 (0.0009)					0.0063*** (0.0014)
Control variable	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	8.7788*** (0.1124)	−0.7303 (3.3829)	−7.4283 (5.0310)	8.7800*** (0.1124)	8.7813*** (0.1127)	0.3641*** (0.0360)	0.8037** (0.3607)	0.5759 (0.4461)	0.3651*** (0.0360)	0.3677*** (0.0359)
R^2	0.5195	0.5280	0.4201	0.4929	0.5181	0.9472	0.5210	0.4946	0.9472	0.9475

Variable	No outworking group					Outworking group				
DEP	−0.0037 (0.0065)	0.2793* (0.1621)	0.3493* (0.1950)	0.0006 (0.0011)	0.0007 (0.0010)	0.0355*** (0.0089)	0.2736*** (0.0963)	0.0290 (0.1288)	0.0354*** (0.0089)	0.0353*** (0.0089)
FPW				−0.0038 (0.0065)					0.0050*** (0.0013)	
FPB					−0.0039 (0.0065)					−0.0006 (0.0018)
Control variable	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	8.7161*** (0.0880)	−1.2712 (2.3321)	−7.8834*** (2.6429)	8.7168*** (0.0880)	8.7212*** (0.0883)	0.1924*** (0.0314)	0.8256** (0.3405)	0.8213* (0.4555)	0.1965*** (0.0314)	0.1929*** (0.0315)
R^2	0.5310	0.7082	0.7079	0.7137	0.7074	0.9674	0.4085	0.4910	0.9675	0.9674

In order to accelerate the digital transformation of the entire agricultural industry chain and promote low-carbon agricultural development with the high-quality development of the rural digital economy, this paper proposes the following policy inspirations: Firstly, the in-depth implementation of the entire agricultural industry chain digital innovation and development project, and improve the mechanism of contacting farmers and driving them. Especially in low-carbon agriculture, improving the construction

TABLE 14 Regression results on the low-carbon effect of farmers' digital economic participation under digital economic inequality.

Variable	CP				
	All samples	Low human capital group	High human capital group	Low age group	High age group
DEP	0.0211*** (0.0034)	0.0216*** (0.0041)	0.0032* (0.0019)	0.0011* (0.0006)	0.0185*** (0.0047)
DP	−0.0034 (0.0027)	−0.0043 (0.0031)	0.0002 (0.0008)	−0.0002 (0.0007)	−0.0030 (0.0032)
DEP × DP	0.0018** (0.0008)	0.0027*** (0.0008)	0.0001 (0.0022)	0.0018 (0.0020)	0.0024*** (0.0008)
Constant	0.4361*** (0.0354)	0.4070*** (0.0363)	8.7743*** (0.1620)	8.5623*** (0.0997)	0.2753*** (0.0348)
Control variable	Controlled	Controlled	Controlled	Controlled	Controlled
Village fixed effect	Controlled	Controlled	Controlled	Controlled	Controlled
R^2	0.9364	0.9453	0.7771	0.8600	0.9604

and operation mechanism of all kinds of digital platforms is more important, accelerating the intelligent transformation of low-carbon agricultural production, management and services and innovating the promotion system of smart agriculture and low-carbon agricultural technology. Secondly, it is to improve digital infrastructure construction and guarantee the fair and universalization of digital dividends. Rural digital infrastructure construction requires special national fiscal funds or policy support, such as tax incentives for relevant operating companies to encourage them to formulate corresponding tariff programs. Moreover, the layout of infrastructure construction should give priority to rural production and living needs and construction costs. Thirdly, improve farmers' digital literacy and their initiative to participate in the digital economy. Relevant government departments need to strengthen farmers' digital awareness through publicity and demonstration. Education and training can be provided across the board to equip farmers with the digital literacy they need to participate in the digital economy. The advanced role of elite rural farmers should also be fully utilized to drive the local population to actively utilize digital technologies. Fourthly, give full play to digital supply and marketing advantages and build a supply chain system with leading enterprises as the main body and deeply integrated small and medium-sized farmers. Taking leading enterprises as the starting point, build a smart low-carbon agricultural database to guide the precise production of low-carbon agriculture and the precise marketing of green agricultural products. In addition, small and medium-sized farmers can use the modern circulation network system established by supply and marketing cooperatives to promote the industrialization development of low-carbon agriculture through contract agriculture.

This paper mainly has the following two limitations: On the one hand, this paper is limited by the complexity of micro-field research leading to the limited number of samples obtained, which may have a certain impact on the research results of this paper, such as failing to fully consider other mediating variables. On the other hand, due to the limitations of cross-sectional data, the conclusions obtained in this paper may be biased. Cross-sectional data can only provide static information at a certain point in time, but cannot reveal the long-term dynamic changes and possible trends after the implementation of policies. In this paper, it is difficult to fully evaluate the long-term effects of farmers' participation in the digital economy and its continued impact on the low-carbon development of agriculture based on cross-sectional data alone. Therefore, in the future, the author will continue to pay attention to the update of the CRRS database to make up for the existing deficiencies by using panel data to build empirical models.

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

XW: Formal analysis, Funding acquisition, Methodology, Project administration, Software, Visualization, Writing – original draft. XL: Resources, Supervision, Validation, 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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