frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 09 January 2026
DOI 10.3389/fsufs.2025.1721636

OPEN ACCESS

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RECEIVED 09 October 2025
REVISED 21 November 2025
ACCEPTED 05 December 2025
PUBLISHED 09 January 2026

CITATION
Pan Q, Yu S, Yang L, Wang L and Yu Y (2026) Nonlinear relationship between digital literacy and Farmers' Straw Incorporation Behavior: evidence from rural China.
Front. Sustain. Food Syst. 9:1721636.
doi: 10.3389/fsufs.2025.1721636

Nonlinear relationship between digital literacy and Farmers' Straw Incorporation Behavior: evidence from rural China

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Background: Ecological security of cultivated land is crucial for the sustainable development of a nation's society and economy.

Methods: Utilizing the 2020 China Rural Revitalization Survey (CRRS) database, organized by the Rural Development Institute of the Chinese Academy of Social Sciences, this study employs nonlinear regression, mediating effect, and moderating effect models to explore the intrinsic relationship between digital literacy and farmers' adoption of straw return practices.

Results: Digital literacy exhibits a U-shaped effect on straw return behavior among farmers, with a threshold value of 0.5. Digital literacy influences straw return in a U-shaped manner by facilitating capital accumulation. Neighborhood interaction delays the inflection point at which digital literacy begins to inhibit straw return, thereby strengthening its suppressive effect and steepening the U-shaped relationship.

Conclusions: Governments should enhance regional digital infrastructure, increase internet accessibility, and focus on improving farmers' financial literacy through targeted training programs to expand their financial knowledge.

KEYWORDS

digital literacy, straw incorporation behavior, nonlinear relationship, neighborhood effects, cultivated land protection

1 Introduction

Cultivated land constitutes the cornerstone for the existence and development of human societies, and significantly influences the sustainable development trajectory of national economies and societies (Liu et al., 2018). However, due to excessive exploitation and irrational utilization of land resources, countries worldwide are confronted with severe ecological degradation of arable land (Gebhardt, 1996; Schulze-Sylvester et al., 2018; Su et al., 2024; Pan et al., 2024). As a conservation tillage practice, straw return demonstrates pronounced factor substitution effects (Sui et al., 2022), crop yield enhancement effects (Hu et al., 2025), and agricultural carbon emission reduction effects (Wang et al., 2012). It is regarded as a crucial measure and practical strategy for achieving cultivated land protection and sustainable agricultural development (Sui et al., 2022). The Chinese government has placed strong emphasis on the ecological conservation of farmland. Since the General Office of the State Council issued the Opinions on Accelerating the Comprehensive Utilization of Crop

Straw in 2008, consecutive policy documents have been promulgated to promote straw utilization. As a result, the comprehensive straw utilization rate in China has increased significantly. According to data from the Ministry of Agriculture and Rural Affairs of China, the national straw utilization rate reached 87.2% by 2024. However, constrained by limitations in labor, capital, and technical endowments (Dong et al., 2024), the adoption of straw return among Chinese farmers remains relatively low (Qiu et al., 2020), and incidents of straw burning remain frequent. This underscores the critical need to address the constraints on straw incorporation, a key step toward advancing both ecological conservation of cultivated land and the sustainability of agricultural systems.

Currently, the digital economy, mediated by digital technologies, has exerted profound impacts on the production and livelihoods of Chinese farmers (Huang et al., 2024). The penetration of digital technologies promotes the optimized allocation of resources in rural areas and incentivizes the improvement of farmers' digital literacy (Gilster and Glister, 1997). The enhancement of digital literacy among farmers presents a dual effect: it strengthens their ability to access information, thereby reducing agricultural production costs, while simultaneously fostering a growing inclination to transition away from farming, which may undermine the sustainability of agricultural operations. Against this backdrop, a critical question emerges: How does digital literacy influence farmers' adoption of straw returning practices? Specifically, this study examines whether improved digital literacy facilitates straw returning by alleviating key constraints—such as labor shortages, financial limitations, and technical barriers—or whether it instead discourages adoption by intensifying farmers' disengagement from agriculture, thereby weakening their commitment to sustainable farm management. Addressing this question is essential to informing the design of effective cropland conservation policies and advancing the goals of agricultural sustainable development, offering both theoretical insights and practical implications.

Current scholarly explorations have extensively examined crop straw incorporation in agricultural practices. Regarding farmers' adoption barriers, improper utilization of crop straw is shown to deteriorate the agricultural production environment and disrupt agroecosystems, thereby posing risks to human health (Jiang et al., 2019). Furthermore, direct straw incorporation may exacerbate crop diseases and pests (Lv et al., 2013) and increase methane emissions (Yao et al., 2013), significantly affecting agricultural productivity and carbon emissions (Yu et al., 2023). Additionally, scholars note that straw incorporation exhibits notable lagged agronomic benefits, which adversely influence farmers' current decision-making regarding technology adoption (Su et al., 2021; Xie and Mu, 2025). Studies on promoting straw incorporation indicate that social support facilitates farmers' adoption of this practice (Jang and Yang, 2023). However, it has also been argued that the positive externality generated by technological spillover effects could raise private costs for farmers, thereby hindering adoption. From the perspective of farm size, Zhang Xing identified that small-scale farmers face more severe labor constraints when adopting straw incorporation (Zhang and Yang, 2021). Other researchers have investigated farmers' willingness and behavior under different compensation schemes (Zhao et al., 2022; Gao et al., 2024). Additional influencing factors include profit expectations (Lv et al., 2015), the public goods nature of environmental benefits (Wang and Cai, 2014), government policies (Guo et al., 2022), farmers' cognitive levels (Zhi and Yan, 2021), and their engagement in off-farm employment (Ke et al., 2022). Within the scholarly discourse on the digital economy's influence on agricultural production, a predominant line of inquiry concentrates on the direct impact of digital literacy on farmers' adoption of green agricultural practices (Wang and Zhang, 2025; Liu et al., 2024). Concurrently, an emerging research stream explores the drivers of protective agricultural practices, proposing that digital literacy serves not merely as a direct predictor but as a positive moderator. It is posited to amplify the effect of farmers' engagement with the digital economy on their subsequent adoption of these conservation-oriented behaviors (Liu M. et al., 2025).

In summary, while substantial research has been conducted on the constraints and influencing factors of straw incorporation, yielding fruitful outcomes, several aspects warrant further reflection. With the advent of the digital era, the digital technology revolution is profoundly reshaping various facets of production and livelihoods. Its potential impact on farmers' adoption of straw incorporation remains an emerging area of inquiry.

In summary, while extensive scholarly attention has been devoted to examining the barriers and influencing factors of straw return practices, yielding substantial insights, two critical dimensions remain underexplored. First, although numerous studies have investigated the role of digital literacy in shaping agricultural production decisions, and some have considered its moderating effect on cropland conservation behaviors, the direct linkage between digital literacy and farmers' adoption of straw return remains inadequately elucidated. Second, given that straw return implementation often involves certain financial and technical thresholds, it is essential to examine whether the relationship between digital literacy and adoption behavior is conditioned by these constraints. To address these gaps, this study draws on nationally representative rural household survey data collected by the Chinese Academy of Social Sciences to empirically investigate the intrinsic relationship between digital literacy and farmers' engagement in straw return practices.

2 Materials and methods

2.1 Theoretical analysis

2.1.1 Intrinsic logic of the nonlinear relationship between digital literacy and farmers' straw incorporation

Digital literacy, initially proposed by Gilster and Glister (1997), refers to an individual's comprehensive capacity to access, process, evaluate, and innovatively apply digital information via digital devices (Gilster and Glister, 1997). In the context of agriculture, farmers' digital literacy can be understood as a multidimensional construct encompassing digital awareness, knowledge, and skills developed during agricultural production (Yang and Zhang, 2024). It reflects the ability to utilize digital technologies to manage, interpret, integrate, communicate, evaluate, and create information. Digital literacy facilitates straw incorporation through three primary mechanisms. First, it enhances farmers' ecological cognition, improves their ability to acquire and utilize ecological information (Liu et al., 2024), and deepens their understanding of environmental policies (Chen et al., 2025), thereby promoting the adoption of straw incorporation. Second, digital literacy strengthens farmers' responsiveness to digital financial services (Sun et al., 2024), fosters human capital accumulation, and improves their ability to prevent digital fraud (Choung et al., 2023). These capabilities enable farmers to access credit information more effectively, alleviating financial constraints associated with straw incorporation. Third, digital literacy improves information acquisition capacity and broadens channels for skill training (Yang et al., 2025), leading to a better understanding of technical specifications and operational procedures of straw incorporation, which in turn supports its effective implementation. Furthermore, digital literacy enhances farmers' risk perception, which promotes the adoption of straw incorporation practices. Given that straw incorporation involves high initial investment, stringent technical expertise requirements, and uncertain returns, sustained implementation largely depends on farmers' ability to perceive and respond to associated risks.

However, straw incorporation also entails high technical thresholds, necessitating a correspondingly higher level of digital literacy (Liu et al., 2024). As rational actors aiming to maximize profits, farmers may not adopt straw incorporation when their technical capacity falls below the required threshold (Liu H. et al., 2025). Instead, improved digital literacy may lead them to engage in straw removal to seek alternative income sources. Empirical evidence also suggests that farmers with lower digital literacy tend to use the internet primarily for social and entertainment purposes, while those with higher digital literacy are more likely to access agricultural extension information, thereby enhancing agricultural productivity. Furthermore, digital literacy may accelerate the shift of labor away from agriculture, potentially undermining the sustainability of agricultural operations. Wang et al. (2024) noted that digital literacy promotes off-farm employment among rural laborers by enhancing human capital, increasing information accessibility, and reducing time spent on domestic chores.

Based on the above analysis, the following hypothesis is proposed:

H1: Digital literacy exhibits a U-shaped effect on farmers' adoption of straw incorporation, initially decreasing and then increasing the likelihood of adoption. Specifically, only when digital literacy reaches a certain threshold will it positively influence straw incorporation.

2.1.2 Mechanism analysis

Given that the adoption of straw recycling is often hampered by financial and technical barriers, this research proposes a plausible pathway through which farmers' digital literacy influences this practice: the channel of capital endowment. The analytical framework first posits that digital literacy enhances farmers' access to and management of financial capital. Subsequently, it introduces social capital into the model, specifically testing the moderating role of neighborhood effects within the community.

Straw return demonstrates significant potential in mitigating environmental pollution, enhancing the efficiency of resource recycling, and improving agricultural productivity. However, its adoption is often constrained by high input costs. Farmers, who typically possess limited capital endowment, may be restricted in implementing straw return practices. Digital literacy, defined as the ability of farmers to adapt to the digital era, can facilitate the adoption of straw return by alleviating capital constraints. First, digital literacy can directly increase household income levels (Chen et al., 2024), thereby promoting capital accumulation. On one hand, it diversifies household financial portfolios (Xu et al., 2024), expands the selection, proportion, and scale of risk assets (Hu and Liu, 2025); on the other hand, it enhances financial knowledge and encourages the use of digital financial services—including mobile payments, online lending, and digital financial products (Yang et al., 2023)—thereby optimizing the household capital structure. Second, digital literacy strengthens household capital resilience. Digital financial literacy significantly improves household financial resilience by alleviating liquidity constraints, increasing risk tolerance, and promoting wealth accumulation (Zhu and Pei, 2024). Finally, digital literacy broadens farmers' income sources. It fosters entrepreneurial activities in rural areas by improving farmers' health status (Bai et al., 2023), and individuals with higher digital literacy exhibit significantly higher entrepreneurial survival rates, thereby expanding off-farm income opportunities (Li and Pan, 2025).

Based on the above, the following hypothesis is proposed:

H2: Capital endowment plays a mediating role in the relationship between digital literacy and farmers' adoption of straw return. That is, digital literacy enhances farmers' capital endowment, which in turn promotes their adoption of straw return.

Neighborhood effects refer to the influence that certain characteristics of a neighborhood exert on individuals' socio-economic outcomes (Wilson, 1987). Initially proposed by sociologist Wilson (Durlauf, 2004), the core concept hinges on "spatial proximity," which fosters frequent interactions and subsequently affects individuals' behavioral choices, attitudes, and access to resources. These effects can be either positive or negative, depending on the quality of relationships and the nature of interactions within the community (Coulton et al., 2009). Owing to neighborhood effects, farmers' production decisions are significantly influenced by the behaviors of surrounding farmers (Liu, 2020). Mutual communication among farmers means that the adoption of green production practices by some can influence—and be influenced by—neighboring farmers, thereby reinforcing confidence in adopting such practices (Zhang et al., 2025). The role of neighborhood effects becomes more pronounced when farmers have more time to interact with their neighbors (Zhang et al., 2023). Due to limitations in personal capability and cognitive levels, as well as the technical barriers associated with straw return, farmers' agricultural practices often align with those of their neighbors (Yang and Ju, 2014). Once surrounding farmers adopt a specific green production technology, individuals are more likely to make similar decisions (Li et al., 2020).

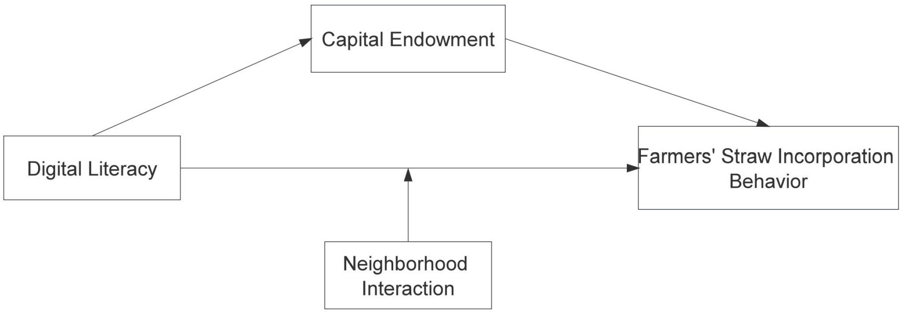

FIGURE 1
Pathways through which digital literacy influences Farmers' Straw Incorporation Behavior.

Accordingly, the following hypothesis is proposed:

H3: Neighborhood effects play a moderating role in the relationship between digital literacy and farmers' adoption of straw return. Specifically, neighborhood effects strengthen the U-shaped impact of digital literacy on straw return adoption.

Figure 1 presents the conceptual framework illustrating the impact of digital literacy on Farmers' Straw Incorporation Behavior.

2.2 Research design

2.2.1 Data source

The data utilized in this study were drawn from the 2020 China Rural Revitalization Survey (CRRS) database, administered by the Institute of Rural Development, Chinese Academy of Social Sciences. Employing a stratified random sampling strategy, the survey encompassed 300 administrative villages and over 3,800 households across 10 provinces in China. The questionnaire covered multiple facets, including agricultural production, land management, the digital economy, rural governance, and resident well-being. The data processing procedure involved the following steps: (1) integrating household and village questionnaires through horizontal matching to facilitate variable selection; (2) excluding households not engaged in agricultural production to align with the research focus on crop straw recycling; and (3) addressing outliers, missing values, and extreme values. Missing data were imputed, and nonparametric estimation methods were applied where appropriate. All continuous variables were winsorized at the 1st and 99th percentiles to mitigate the influence of extreme observations. The final analytical sample comprised 1,769 valid observations.

2.2.2 Construction of the digital literacy index system

Drawing on Gilster and grounded in the analytical framework of the first- and second-level digital divides, this study conceptualizes farmers' digital literacy across two dimensions: digital acquisition and digital application. These dimensions are operationalized through 5 secondary indicators and 14 tertiary indicators. The digital acquisition dimension, corresponding to the first-level digital divide, assesses digital access literacy via 3 indicators. The digital application dimension, reflecting the second-level digital divide, encompasses four aspects: digital communication literacy, digital commercial literacy, digital information literacy, and digital problem-solving literacy, measured by 11 indicators. In this study, digital media literacy draws on Hu and Sun's (2022) conceptualization of digital foundational skills and is defined as a household's capacity to access digital technologies. Since other forms of literacy often operate through the use of communication tools such as mobile phones and the internet, digital media literacy constitutes a foundational dimension of overall digital literacy. It is measured using the following survey items: "Does your household own internet-enabled devices?", "How many 4G/5G mobile phones does your household possess?", and "Do you use a 4G/5G mobile phone?" Digital information literacy builds on Zurkowski's (1974) definition of information literacy as "the techniques and skills learned through using a wide range of information tools and primary sources in solving problems." We define it as the willingness and ability to use the internet to acquire information that meets productive and daily living needs. This construct is captured by three survey questions: "Do you prefer that the village committee disseminate important information via online channels?", "To what extent does online information satisfy your production and daily needs?", and "When you have routine needs, can you independently obtain relevant information using a mobile phone or the internet?" Digital social literacy follows Bawden's (2001) notion of network literacy, which refers to the ability to understand, analyze, evaluate, and utilize online resources to acquire, disseminate, and generate information. We adapt this to rural contexts as the capacity of farm households to engage in social interactions through digital platforms to access, share, and create information. It is measured by: "Do you use mobile phones or the internet for chatting and social networking?" and "Have you ever used WeChat groups to discuss important public affairs within your village?" Digital commercial literacy centers on farm households' transactional needs and reflects their ability to use mobile and internet technologies in productive and consumption activities. It is assessed through: "Does your household sell products online?", "Are you willing to sell your products online?", and "Do you use mobile internet for transactions?" Lastly, digital problem-solving literacy is informed by the EU Digital Competence Framework's dimension on problem-solving, which emphasizes the ability to identify information needs, select appropriate digital tools, solve problems through digital means, use technologies innovatively, and handle technical issues. We define it as a household's capacity to resolve problems using mobile or internet technologies. It is measured by: "Do you encounter difficulties in using various functions of 4G/5G mobile phones?" and "Do you browse news via mobile or internet?" These items reflect that mobile functionalities can enhance problem-solving abilities, while news consumption often exposes users to potential market demands and practical information. To comprehensively evaluate farmers' digital literacy, factor analysis was employed to reduce dimensionality. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy yielded a value of 0.774 (exceeding the threshold of 0.6), and Bartlett's test of sphericity was significant ($p < 0.001$), confirming the suitability of the data for factor analysis. Five common factors with eigenvalues greater than 1 were extracted, cumulatively explaining 62.1% of the total variance. All indicator covariance coefficients remained below 0.6, demonstrating satisfactory validity and effective representation of both digital acquisition and application constructs. Finally, factor scores were standardized to eliminate negative values. The detailed index system is presented in Table 1.

TABLE 1 Construction of digital literacy index system for farmers.

Primary indicator	Secondary indicator	Tertiary indicator
Digital access	Digital media literacy (A)	Household possession of internet-enabled devices (A_1)
		Number of 4G/5G smartphones owned by the household (A_2)
		Personal use of 4G/5G smartphones (A_3)
Digital application	Digital information literacy (B)	Preference for receiving important village announcements via digital channels from the village committee (B_1)
		Perceived adequacy of online information for fulfilling daily production and livelihood needs (B_2)
		Ability to independently access necessary information via smartphone or internet when needed (B_3)
	Digital social literacy (C)	Engagement in chat-based social interactions via mobile or online platforms (C_1)
		Participation in WeChat group discussions concerning important village public affairs (C_2)
	Digital commercial literacy (D)	Household engagement in online sales of agricultural or other products (D_1)
		Willingness to adopt e-commerce platforms for product sales (D_2)
		Utilization of mobile internet for conducting transactions (D_3)
		Aspiration to pursue employment or entrepreneurship opportunities through mobile internet (D_4)
	Digital problem-solving literacy (E)	Perceived difficulties in utilizing 4G/5G smartphone functionalities (E_1)
		Engagement in news browsing via mobile or online platforms (E_2)

2.2.3 Variable selection and statistical description

2.2.3.1 Dependent variable

The dependent variable in this study is straw return. This is measured through the survey questions: "Does your household grow crops that produce straw?" and "If yes, how do you currently handle the straw?" Based on the responses, a household is considered to practice straw return if it both grows straw-producing crops and disposes of the straw by means of crushing and returning it to the field. Otherwise, the household is classified as not engaging in straw return.

2.2.3.2 Core explanatory variable

The core explanatory variable is farmers' digital literacy, which is constructed based on the indicator system developed above. The level of digital literacy is quantified using factor analysis and principal component analysis.

2.2.3.3 Mechanism variables

As discussed in the introduction, this study examines the mediating effect of capital endowment and the moderating effect of neighborhood interaction. Capital endowment is measured by the total amount of household deposits and digital wallet balances (e.g., WeChat or Alipay) at the end of the year. Neighborhood interaction is captured by whether a farmer receives mutual assistance from neighbors in agricultural activities.

2.2.3.4 Control variables

Drawing on established literature (Wang, 2024; Hua and Pan, 2024), control variables are selected across three dimensions: Individual characteristics of the household head (gender, age, education level, health status); Household characteristics (whether the family operates a farm, participates in a cooperative, has agricultural insurance, total cultivated area, and receipt of agricultural subsidies); Village characteristics (village location, educational level of the village secretary, village topography, and property rights reform).

2.2.3.5 Instrumental variable

The provincial average digital literacy level (excluding the farmer's own province) is used as an instrumental variable to address potential endogeneity in the econometric model.

Detailed variable definitions, value assignments, and descriptive statistics are provided in Table 2.

2.2.4 Specification of econometric models

2.2.4.1 Baseline regression model

To examine the impact of digital literacy on farmers' adoption of straw incorporation technology, the following baseline regression model is established:

$$FSIB_i = \beta_0 + \beta_1 Dig_i + \beta_2 Dig_i^{\,2} + \gamma Control + \varepsilon_i \tag{1}$$

where $FSIB_i$ denotes the adoption of green technology by household; Dig_i and $Dig_i^{\,2}$ represent the linear and quadratic

TABLE 2 Variable definition and descriptive statistics.

Variable category	Variable name	Symbol	Definition	Mean	Std. dev.
Dependent variable	Farmers' Straw Incorporation Behavior	FSIB	Dummy variable: 1 if the household adopts straw incorporation practices; 0 otherwise.	0.499	0.500
Core explanatory variable	Digital literacy level	Dig	Composite index of digital literacy, constructed using factor analysis with weighted components.	0.406	0.157
Mediating variable	Capital endowment	Cap	Total household liquid assets at year-end, including deposits and balances in WeChat and Alipay (Yuan).	8.816	15.182
Moderating variable	Neighborhood interaction	Net	Dummy variable: 1 if the household engages in mutual assistance with neighbors in agricultural production; 0 otherwise.	0.672	0.470
Instrumental variable	Provincial mean digital literacy	Dig-pr	Mean digital literacy score at the provincial level, excluding the farmer's own province (continuous).	0.406	0.039
Control variables	Gender	Gend	Gender of the household head: 1 = Male; 2 = Female.	1.046	0.210
	Age	Year	Age group of the household head: 1 = 18–45 years; 2 = 45–60 years; 3 = >60 years.	2.260	0.684
	Education level	Educ	Educational attainment of the household head: 1 = No formal schooling; 2 = Primary or junior high school; 3 = Senior high school, vocational school, or technical secondary school; 4 = College degree or higher.	2.059	0.518
	Health status	Heth	Self-reported health status of the household head: 1 = Poor; 2 = Fair; 3 = Good.	2.436	0.722
	Family farm operation	Farm	Dummy variable: 1 if the household operates a family farm; 0 otherwise.	0.037	0.188
	Cooperative membership	Coop	Dummy variable: 1 if the household participates in a farmer cooperative; 0 otherwise.	0.230	0.421
	Agricultural insurance	Insr	Dummy variable: 1 if the household purchases agricultural insurance; 0 otherwise.	0.446	0.497
	Total operated land area	Scar	Total land area operated by the household (Mu).	14.493	15.131
	Agricultural subsidies	Subs	Total amount of governmental crop subsidies received by the household in the current year (Yuan).	2,321.579	7,671.060
	Village location	Loct	Dummy variable: 1 if the village is located in a suburban area; 0 otherwise.	1.837	0.370
	Village party secretary's education	Edu-vr	Educational level of the village party secretary: 1 = Primary or junior high school; 2 = Senior high school, vocational school, or technical secondary school; 3 = College degree or higher.	2.101	0.778
	Village topography	Tera	Topography of the village: 1 = Plain; 2 = Hilly; 3 = Mountainous.	2.181	1.315
	Property rights reform	Refo	Status of land property rights reform in the village: 1 = Not yet started; 2 = Ongoing; 3 = Completed.	2.591	0.643

terms of digital literacy, respectively; *Control* is a vector of control variables; β_0 is the intercept; β_1 and β_2 are the coefficients of interest for the core explanatory variable and its quadratic term; γ denotes the coefficients of the control variables; and ε_i is the stochastic error term.

2.2.4.2 Mediation effect model

To investigate the potential mediating effect of capital endowment in the relationship between digital literacy and straw incorporation, a nonlinear mediation model is specified as follows:

$$Mediating_i = \beta_0 + \beta_1 Dig_i + \beta_2 Dig_i^{\,2} + \gamma Control + \varepsilon_i \tag{2}$$

where $Mediating_i$ represents the mediating variable, capital endowment. A significant estimate of β_1 or β_2 would indicate that digital literacy influences capital endowment.

2.2.4.3 Moderation effect model

To assess the moderating role of neighborhood interaction in the relationship between digital literacy and straw incorporation, following Wang and Liu (2025), interaction terms between neighborhood interaction and both the linear and quadratic terms of digital literacy are incorporated into the baseline model:

$$\begin{aligned} FSIB_i = {} & \beta_0{}' + \beta_1 Dig_i + \beta_2 Dig_i^{\,2} + \beta_3 Net + \beta_4 Dig_i \times Net \\ & + \beta_5 Dig_i^{\,2} \times Net + \gamma_1 Control + \varepsilon_i \end{aligned} \tag{3}$$

Here, *Net* denotes neighborhood interaction. The coefficients $Dig_i \times Net$ and $Dig_i^{\,2} \times Net$ capture the moderating effect. If either is statistically significant, it suggests that neighborhood interaction moderates the influence of digital literacy on straw incorporation.

TABLE 3 Analysis of regression results.

Variable	Farmers' Straw Incorporation Behavior			
	(1)	(2)	(3)	(4)
Dig	−3.340***	−0.830***	−3.298***	−0.702***
	(1.058)	(0.260)	(1.145)	(0.242)
Dig2	4.040***	1.004***	3.312**	0.705**
	(1.377)	(0.339)	(1.458)	(0.309)
Gend			0.064	0.014
			(0.245)	(0.052)
Year			0.114	0.024
			(0.089)	(0.019)
Educ			0.334***	0.071***
			(0.106)	(0.022)
Heth			0.177**	0.038**
			(0.073)	(0.015)
Farm			0.395	0.084
			(0.294)	(0.062)
Coop			0.470***	0.100***
			(0.126)	(0.026)
Insr			0.062	0.013
			(0.111)	(0.024)
Scar			−0.003***	−0.001***
			(0.001)	(0.000)
Subs			0.000	0.000
			(0.000)	(0.000)
Loct			−0.012	−0.003
			(0.141)	(0.030)
Edu-vr			−0.034	−0.007
			(0.069)	(0.015)
Tera			−0.582***	−0.124***
			(0.045)	(0.008)
Refo			−0.259***	−0.055***
			(0.082)	(0.017)
_cons	0.585***		1.195*	
	(0.202)		(0.656)	
N	1,769		1,768	
adj.R^2	0.04		0.113	

Standard errors in parentheses *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

3 Results

3.1 Baseline regression results

The baseline regression results are presented in Table 3. Models (1) and (3) examine the effect of digital literacy on farmers' straw return adoption, with Model (1) excluding control variables and Model (3) incorporating controls such as gender and other covariates. The results indicate that both the linear and quadratic terms of digital literacy are statistically significant at the 1% level, regardless of whether control variables are included. The coefficient of the linear term is negative, while that of the quadratic term is positive, suggesting a U-shaped relationship between digital literacy and the adoption of straw return technology. Specifically, at lower levels of digital literacy, an increase in literacy reduces the probability of adopting straw return. However, after a certain threshold is surpassed, further improvement in digital literacy promotes adoption, thus supporting Hypothesis 1. The results from Models (2) and (4), which include control variables, reveal a statistically significant nonlinear relationship between digital literacy and farmers' adoption of straw return. Specifically, before digital literacy reaches a critical threshold, a 1% increase is associated with a 0.702% decrease in the probability of adoption. Conversely, after surpassing this threshold, a 1% increase in digital literacy correlates with a 0.705% increase in the likelihood of adoption. This pattern may be attributed to the technical and financial barriers associated with straw return. When farmers' digital literacy is relatively low, they tend to prioritize short-term economic gains and may prefer alternative disposal methods such as straw removal. As digital literacy reaches a higher level, farmers become more aware of the long-term ecological benefits and yield-enhancing effects of straw return.

3.2 Robustness checks

3.2.1 Utest procedure

The baseline regression results indicate that the linear term of digital literacy is significantly negative, while its quadratic term is significantly positive, suggesting a potential U-shaped relationship between digital literacy and farmers' straw return behavior. However, the significance of both the linear and quadratic terms alone does not sufficiently establish a U-shaped pattern, as a convex or concave monotonic relationship could also produce a significant quadratic coefficient, potentially leading to misidentification. To mitigate such bias and rigorously validate the inverted U-shaped relationship, we further employ the Utest method. As reported in Table 4, the slope of digital literacy spans the interval (−0.703, 0.704) within the specified model. This range includes positive values, providing support for an inverted U-shaped curve. Moreover, the overall test statistic is significant at the 1% level, confirming a statistically significant inverted U-shaped relationship between digital literacy and straw return adoption.

3.2.2 Alternative model specification

To further assess the robustness of the baseline regression results, we re-estimate the model using a Probit specification. The results continue to support an inverted U-shaped relationship between digital literacy and farmers' adoption of straw return practices, confirming that the findings are robust to alternative estimation approaches. Table 5 reports the results of the replacement model.

TABLE 4 Utest test results.

Variable	Farmers' Straw Incorporation Behavior	
	Lowerbound	Upperbound
Extremepoint	0.500	
Interval	0	1
Slope	−0.703	0.704
Overall test of presence of a Ushape		
t-value	1.75	
P>|*t*|	0.04	

TABLE 5 Replace model test results.

Variable	Logit	Probit
	(1)	(2)
Dig	−3.298***	−2.018***
	(1.145)	(0.692)
Dig^2	3.312**	2.029**
	(1.458)	(0.877)
_cons	1.195*	0.733*
	(0.656)	(0.397)
N	1768	1768
adj.R^2	0.113	0.113

Standard errors in parentheses $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 6 Change the sample size regression results.

Variable	The scale is truncated by 10% on both sides	Removing the youth sample	Remove highly educated samples
	(1)	(2)	(3)
Dig	−3.048**	−4.208***	−3.676***
	(1.309)	(1.280)	(1.221)
Dig^2	3.539**	4.773***	3.946**
	(1.689)	(1.706)	(1.590)
Control variable	Controlled	Controlled	Controlled
_cons	1.789**	1.337*	1.280
	(0.746)	(0.743)	(0.787)
N	1457	1527	1527
adj.R^2	150	0.112	0.121

Standard errors in parentheses $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.2.3 Sample adjustment

To mitigate the potential influence of outliers on model estimation, the agricultural operating area data were winsorized at the 10% level in both tails, as specified in Model (1). Furthermore, considering the demographic profile of China's agricultural sector—where middle-aged and older individuals constitute the majority of farmers and overall educational attainment is relatively low—this study additionally conducts robustness checks by excluding younger farmers and highly educated individuals from the sample, corresponding to Model (2) and Model (3), respectively. The estimation results after sample adjustments are presented in Table 6. It can be observed that the significant U-shaped relationship between farmers' digital literacy and straw return behavior remains consistent across various sample compositions, supporting the robustness of the main findings.

3.2.4 Endogeneity test

To address potential endogeneity in digital literacy, this study employs the average level of digital literacy at the provincial level (excluding the individual farmer's own data) as an instrumental variable (IV). The selected instrument is the average digital literacy level at the provincial level, calculated by excluding the focal household itself. The validity of this instrument is justified on two grounds. First, it satisfies the relevance condition. Provincial-level digital literacy reflects regional development in digital infrastructure and the digital economy, which correlates strongly with an individual household's digital literacy. Second, the exclusion restriction is plausibly met. While provincial digital literacy may influence household adoption of straw return practices, any such effect operates primarily through its impact on the household's own digital literacy—rather than through other direct channels affecting adoption behavior. Given that straw return adoption is a binary choice variable, the Conditional Mixed Process (CMP) approach is applied to correct for endogeneity. The CMP method assesses the presence of endogeneity through a test parameter; if this parameter is statistically significantly different from zero, endogeneity is confirmed, and CMP estimation is appropriate. If not, the baseline model estimates are deemed reliable. Table 7 presents the CMP estimation results. Statistical tests support the strength of the instrument. The F-statistic from the first-stage regression is 97.18, well above the conventional threshold of 10, effectively ruling out concerns regarding weak instrument bias. The first-stage regression indicates a significant positive effect of the instrumental variable on farmers' digital literacy. Moreover, the endogeneity test parameter (atanhrho_12) is statistically significant, confirming the presence of endogeneity and justifying the use of the CMP approach. The second-stage CMP results show that, after controlling for endogeneity, digital literacy continues to exhibit a significant inverted U-shaped relationship with farmers' straw return adoption.

3.3 Mechanism analysis

After establishing the impact of digital literacy on farmers' adoption of green technologies, this study further examines the underlying mechanisms through which digital literacy influences such adoption behaviors. The regression results are presented in Table 8.

Model (1) reports the mediating effect of capital endowment. Digital literacy shows a statistically significant positive coefficient at the 10% level. However, when the quadratic term is included,

TABLE 7 CMP estimates of results.

Variable	Provincial mean digital literacy	Farmers' Straw Incorporation Behavior
	Phase one	Phase two
	(1)	(2)
Dig		−5.054***
		(0.800)
Dig^2		1.547*
		(0.839)
Instrumental variable	0.913***	
	(0.093)	
Control variable	Controlled	Controlled
_cons	0.035	
	(0.038)	
atanhrho_12	0.671***	
	(0.147)	
LR	705.6***	
N	1,769	

Standard errors in parentheses $^{*}p < 0.1$, $^{***}p < 0.01$.

TABLE 8 Test of mediating effect of capital endowment.

Variable	Intermediary effect test	Test of adjustment effect	
	Cap	Farmers' Straw Incorporation Behavior	Farmers' Straw Incorporation Behavior
	(1)	(2)	(3)
Dig	1.830*	−3.789***	−7.774***
	(1.020)	(1.181)	(2.045)
Dig^2	−0.341	3.872***	9.962***
	(1.303)	(1.491)	(2.859)
Cap		0.041**	
		(0.017)	
Cap^2		−0.001**	
		(0.000)	
Net_Dig			6.455***
			(2.476)
Net_Dig^2			−9.260***
			(3.353)
Control variable	*Controlled*	*Controlled*	*Controlled*
_cons	−1.484**	−2.761***	1.776**
	(0.750)	(0.887)	(0.716)
N	1,768	1,768	1,768
adj.R^2	0.089	0.146	0.116

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
A note is appended to the table clarifying the specification of the moderating effects. In Model (2), the estimated coefficients (−3.789, 3.872, 0.041, and −0.001) correspond to parameters β1, β_2, β3, and β4 in Equation (3), respectively. Model (3) follows the same functional form, with its coefficients likewise representing the estimates for β1 through β4 in Equation (3).

it fails to achieve statistical significance, indicating that digital literacy has a significant positive effect on capital endowment. This suggests that higher levels of digital literacy enhance farmers' capacity for capital accumulation, thereby supporting Hypothesis 2. Subsequently, Model (2) incorporates capital endowment as a control variable into the relationship between digital literacy and straw return adoption to test its mediating role. The results show that the linear term of capital endowment is significantly positive at the 10% level, while the quadratic term is significantly negative. This implies that digital literacy exerts a U-shaped influence on straw return behavior by facilitating capital accumulation. A possible explanation is that straw return entails technical and financial thresholds. Only when farmers' digital literacy reaches a certain level do they place greater emphasis on the long-term ecological and yield-increasing benefits of straw return. Beyond this threshold, improved digital literacy alleviates financial constraints by enhancing capital accumulation, thereby promoting adoption.

Model (3) examines the moderating role of neighborhood interaction. As hypothesized, neighborhood interaction may moderate the relationship between digital literacy and straw return adoption. Given the established U-shaped relationship between digital literacy and straw return, the moderating effect of neighborhood interaction should account for potential nonlinearities. Following the approach of Wang (2024), Equation (3) is differentiated to identify the inflection point Dig* where the first derivative equals zero. The partial derivative with respect to Net is then computed as follows:

$$Dig^* = \frac{\beta_1 + \beta_4}{2(\beta_2 + \beta_5 Net)}; \frac{\partial Dig^*}{\partial Net} = \frac{\beta_1\beta_5 - \beta_2\beta_4}{2(\beta_2 + \beta_5 Net)^2} \tag{4}$$

As shown in the results of Model (3), the interaction term between the linear term of digital literacy and neighborhood interaction is significantly positive, while the interaction term between the quadratic term of digital literacy and neighborhood interaction is significantly negative. This indicates that neighborhood interaction indeed moderates the U-shaped relationship between digital literacy and farmers' adoption of straw return. The calculated threshold value, derived from the formula $\beta_1\beta_5 - \beta_2\beta_4 = (-7.774) \times (-9.26)\text{-}9.962 \times 6.455$, is positive. The overall curve shifts rightward, implying that the inclusion of neighborhood interaction delays the turning point at which digital literacy begins to promote straw return adoption. That is, it strengthens the inhibitory effect of digital literacy on straw return in the lower range. Moreover, the positive coefficient (7.68253) of the quadratic interaction term further accentuates the curvature of the U-shaped relationship, making it steeper. A possible explanation lies in the fact that farmers with higher digital literacy can efficiently access technical knowledge about straw return through digital platforms. Through interactions with neighbors, they further verify the effectiveness of such knowledge, thereby enhancing their confidence and willingness to adopt the practice.

Additionally, these farmers often act as "local innovators" in promoting straw return techniques. The social recognition gained from diffusing technology serves as a non-economic incentive, encouraging deeper technical exploration and application. This accelerates the upward trend on the right side of the U-shaped curve. On the contrary, farmers with lower digital literacy have limited ability to acquire information through digital channels. In their case, neighborhood interactions may amplify perceptions of uncertainty and skepticism regarding new technologies, thereby reducing their adoption intention. Consequently, on the left side of the U-shaped curve, the straw return adoption behavior of less digitally literate farmers exhibits a notable decline.

3.4 Heterogeneity analysis

3.4.1 Urban–rural heterogeneity test

Given the imbalanced development between urban and rural areas and obstacles to the flow of production factors, significant disparities exist in straw return practices between suburban and remote rural regions. Such geographical heterogeneity may consequently lead to differential impacts of farmers' digital literacy on the development of scaled management operations. Yang contends that suburban farming households are confronted with constraints such as limited land availability and elevated rental costs, rendering them more susceptible to market demand fluctuations (Yang et al., 2025). Accordingly, this study examines the effect of digital literacy on the adoption of green technologies by farmers from an urban–rural comparative perspective. To address the limited sample size of suburban rural households, we employed a bootstrapping technique with 1,000 replications to assess the robustness of our estimates. Table 9 presents the results of the urban–rural heterogeneity analysis. The findings indicate that in remote rural areas, a U-shaped relationship between digital literacy and straw return adoption remains valid. In contrast, in suburban villages, the effect of digital literacy on straw return is not statistically significant.

TABLE 9 Urban-rural disparities.

Variable	Suburban rural areas	Remote rural areas	
	(1)	(2)	(3)
Dig	−3.309***	−3.301	−3.301
	(1.228)	(3.225)	(4.077)
Dig^2	3.067*	4.075	4.075
	(1.573)	(4.003)	(4.994)
Control variable	*Controlled*	*Controlled*	*Controlled*
_cons	0.870	3.832**	3.832
	(0.647)	(1.753)	(2.336)
N	1479	289	289
adj.R^2	0.104	0.198	0.198

Standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A plausible explanation is that in remote rural regions, where information accessibility is relatively limited and traditional agricultural technology dissemination channels are scarce, farmers with higher digital literacy are more proactive in using internet platforms to acquire knowledge about straw return techniques. Through neighborhood demonstrations and social interactions, they develop stronger recognition of the technology, thereby increasing their willingness to adopt it. Hence, in these areas, digital literacy serves as an informational enabling tool that significantly promotes technology adoption after reaching a certain threshold, exhibiting a U-shaped curve. On the other hand, in suburban rural areas, diverse information channels and a well-established agricultural technology extension system provide farmers with ample opportunities to access technical information through offline training, agribusiness services, and government promotions. Consequently, their reliance on digital channels is relatively lower. In such contexts, the level of digital literacy does not directly determine farmers' technology adoption behavior.

3.4.2 Regional heterogeneity test

Significant regional disparities exist across China in terms of economic development, topographic characteristics, digital infrastructure, and resource endowments. These differences may lead to varying impacts of farmers' digital literacy on straw return practices, particularly regarding its hypothesized U-shaped effect. Yu underscores that the eastern region of China demonstrates superior development in its digital infrastructure, along with a higher rate of internet penetration, compared to central and western areas (Yu et al., 2024). To examine this regional heterogeneity, we further test the U-shaped relationship between digital literacy and straw return based on geographic regions. Given the limited number of rural observations from the eastern region, we employed a bootstrap procedure with 1,000 replications to enhance the robustness of our estimates. The results of the regional heterogeneity analysis are presented in Table 10. The findings indicate that the U-shaped effect of digital literacy on straw return remains significant in the eastern region. In contrast, the effects in the central and western regions are statistically insignificant. Several factors may explain these disparities:

First, the eastern region benefits from a stronger economic foundation and more comprehensive digital infrastructure, providing farmers with greater access to digital learning and application tools. Enhanced digital literacy helps broaden information channels and improve learning capacity, thereby facilitating the adoption of agricultural technologies. In comparison, central and western regions exhibit lower internet coverage and limited digital service availability. Even when farmers possess certain digital skills, the lack of adequate devices or supportive environments hinders the effective application of these skills in agricultural production.

Second, the eastern region generally possesses more well-established agricultural technology extension systems, complemented by substantial offline training and policy support. Farmers with higher digital literacy can more effectively integrate online information with offline practices, leading to a more comprehensive and reliable understanding of technologies

TABLE 10 Area differentiation.

Variable	Central region	Western region	Eastern region	
	(1)	(2)	(3)	(4)
Dig	1.973	−2.308	−6.279**	−6.279*
	(2.295)	(1.800)	(3.200)	(3.544)
Dig^2	−1.122	2.585	9.150**	9.150*
	(2.796)	(2.185)	(4.514)	(5.298)
	1.973	−2.308	−6.279**	−6.279*
Control variable	*Controlled*	*Control variable*	*Controlled*	*Controlled*
_cons	2.769**	1.059	−0.930	−0.930
	(1.181)	(1.004)	(2.093)	(2.487)
N	633	802	333	333
adj.R^2	0.119	0.101	0.293	0.293

Standard errors in parentheses $^*p < 0.1$, $^{**}p < 0.05$.

such as straw return. Conversely, central and western regions suffer from relatively scarce extension resources and insufficient institutional mechanisms to translate digital knowledge into practical application, limiting the role of digital literacy in promoting technology adoption.

Third, information flows more readily in rural areas of the eastern region, where frequent interactions among villagers enable digitally literate farmers to act as hubs of technological information, generating diffusion effects. In central and western regions, however, information transmission still relies heavily on traditional interpersonal networks, with digital channels playing a limited role. In some cases, local communication may even reinforce skepticism toward new technologies, attenuating the potential positive influence of digital literacy.

4 Discussion

Cultivated land ecological security is crucial for the sustainable socioeconomic development of all nations. As the largest developing country globally, China has accelerated its agricultural and rural modernization in recent years, achieving remarkable progress. However, due to its national conditions—characterized by a relatively small proportion of arable land and a large population—issues such as overuse and severe degradation of cultivated land persist. Straw return, as a form of conservation tillage, holds significant practical importance for promoting cultivated land protection and sustainable use. Accordingly, using data from the 2020 China Rural Revitalization Survey (CRRS) conducted by the Chinese Academy of Social Sciences, this study examines the relationship between digital literacy and farmers' adoption of straw return within the context of contemporary Chinese agriculture and rural development.

This study finds that digital literacy influences farmers' straw disposal decisions, which is consistent with the findings of Wang and Yan (2023). From a cost-benefit perspective, Wang argued that removing straw from the field tends to generate greater economic returns due to the technical requirements and high costs associated with straw return. He indicated that information literacy reduces the cost of straw removal, thereby promoting its off-field utilization. This study acknowledges that at lower levels of digital literacy, farmers' inclination toward straw return is suppressed. Acting as rational actors, farmers are initially more influenced by the short-term economic benefits of straw removal. However, as digital literacy reaches a certain threshold, ecological benefits and long-term economic gains become prioritized. Farmers with higher digital literacy can easily access technical knowledge about straw return through digital platforms and validate its effectiveness via neighborhood interactions, thereby strengthening their acceptance of the practice and promoting its adoption.

Furthermore, Li's study identifies digital literacy as a significant driver of farmers' adoption of green production technologies, thereby enhancing the intensity of such adoption (Li et al., 2025). He also highlights the positive mediating role of social networks in influencing both the decision and the extent of technology uptake—a finding that resonates conceptually with the moderating effect of neighborhood interaction observed in our research. New agricultural technologies often gain credibility and reduce perceived risks through localized social learning, fostering a form of risk-sharing community that alleviates psychological barriers to adoption. However, by framing social networks primarily as a mediating mechanism, Li's approach may underemphasize other critical determinants influencing farmers‘ adoption behaviors. Smallholders often operate under substantial capital constraints, which elevate the cost of trial-and-error associated with new practices. Future analyses would benefit from incorporating factors such as financial accessibility to offer a more structurally complete explanation.

Addition, this study reveals that capital endowment mediates the U-shaped relationship between digital literacy and straw return adoption, a finding consistent with Liu H. et al. (2025). New technologies often entail high initial costs, low short-term returns, and extended payback periods. Financial constraints frequently hinder farmers' adoption of such technologies. Digital literacy facilitates capital accumulation by improving farmers' access to and comprehension of credit information, as well as enhancing their employment and income-generating capabilities. This alleviates financial barriers and promotes the adoption of new technologies.

Consequently, it is imperative for governments to strengthen digital infrastructure development, with particular emphasis on bridging the digital divide between urban and rural areas. Enhancing digital accessibility in remote agricultural regions will amplify the role of digital literacy in promoting farmers' adoption of straw returning technology. Concurrently, establishing comprehensive digital training systems—including specialized programs integrating digital skills with straw returning techniques—can effectively alleviate technical barriers to adoption, thereby facilitating cropland conservation and sustainable agricultural development. Furthermore, developing robust online platforms is essential to disseminate information on favorable loan policies for farmers. Initiatives such as a "Technology Innovation Loan" targeted at households adopting straw returning could help alleviate financial constraints in production, thereby supporting broader adoption of sustainable practices.

4.1 Marginal contributions

First, this study constructs a digital literacy index system comprising two dimensions (digital access and digital application), five secondary indicators, and fourteen tertiary indicators, providing a comprehensive assessment of farmers' digital literacy. Second, it develops an analytical framework of "digital literacy–farmers' straw return" to explore the nonlinear relationship between these variables, clarifying the mechanisms through which digital literacy influences straw return adoption. This offers theoretical insights for promoting cultivated land protection and agricultural sustainability in China and other countries facing similar challenges. Third, by testing mechanisms involving the mediating role of capital endowment and the moderating role of neighborhood interaction, this study elucidates the pathways through which digital literacy affects straw return, providing policy recommendations for encouraging farmers' adoption of straw return practices.

4.2 Limitations

First, this study employs cross-sectional data from the 2020 CRRS, which is relatively dated and does not capture dynamic changes in the relationship between digital literacy and straw return. Nonetheless, this dataset was selected as it comprehensively covers indicators relevant to our research questions. Although a more recent survey (2022) was conducted, the data are not yet accessible. Concurrently, we plan to leverage a longitudinal survey of farm households conducted within our provincial research framework. This localized micro-level dataset will be instrumental in providing deeper empirical validation of the relationship between digital literacy and the adoption of straw incorporation, thereby supplementing and cross-verifying the findings derived from broader national data. Second, while a nonlinear relationship is identified, the use of cross-sectional data precludes the application of a robust threshold regression model to estimate precise threshold effects. Third, the model does not incorporate climate change variables. Given the increasing frequency of extreme climate events and their impacts on agricultural production, future studies should include climate indicators, contingent on data availability.

4.3 Future research directions

First, panel data should be used to re-examine the nonlinear relationship and apply threshold models to accurately estimate the threshold effects of digital literacy on straw return. Second, climate change variables should be integrated into the model to account for the growing influence of extreme weather events on agricultural decision-making.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The data used in this study are from a survey conducted by the Chinese Academy of Social Sciences. Our team signed a confidentiality agreement before using the data, so we cannot directly provide the original data. Requests to access these datasets should be directed to Chinese Academy of Social Sciences.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the (patients/participants OR patients/participants legal guardian/next of kin) was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

QP: Project administration, Writing – original draft, Writing – review & editing, Funding acquisition, Visualization, Conceptualization, Methodology, Validation. SY: Conceptualization, Methodology, Software, Funding acquisition, Project administration, Writing – review & editing, Writing – original draft. LY: Supervision, Writing – review & editing, Validation, Formal analysis. LW: Investigation, Validation, Writing – review & editing. YY: Writing – review & editing, Investigation, Resources.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This research was funded by Special Project on Digital Economy Research at Nanchang Business College of Jiangxi Agricultural University: Pathways to High-Value Development in Jiangxi's Manufacturing Sector Through Digital Economy Integration, Grant Number NSSJ2101.

Conflict of interest

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

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