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Can internet use promote farmers' diversity in green production technology adoption? Empirical evidence from rural China

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Agricultural non-point source pollution significantly threatens global ecosystems and sustainable agricultural development. Adopting diversified green production technologies is recognized as a key approach to mitigating agricultural pollution and promoting sustainability. Internet use (IU) has become essential for promoting farmers' diversity in green production technology adoption (DIGPTA) and mitigating agricultural non-point source pollution. Although many studies have analyzed the impact of IU on agricultural green production technologies, the relationship between IU and farmers' DIGPTA remains poorly understood. In particular, the mechanism by which IU influences farmers' DIGPTA remains unclear. Based on the micro-survey data from the China Land Economy Survey (CLES) conducted between 2020 and 2022, this study employs the IV-Tobit model to investigate how IU affects farmers' DIGPTA and its underlying mechanisms. The findings indicate that: (1) IU is significantly correlated with farmers' DIGPTA. Farmers' DIGPTA increases by 53.10% as IU increases by one unit. (2) When grouped by generational differences, IU substantially influences the DIGPTA of new-generation farmers. (3) IU enhances farmers' DIGPTA by influencing their decision-making preferences, environmental awareness, and diversification risk perception. The mediating effects of decision-making preferences, environmental awareness, and diversification risk perception on farmers' DIGPTA are 11.90%, 6.79%, and 16.84%, respectively. These findings have important implications for addressing agricultural non-point source pollution and promoting sustainable agricultural development.

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Introduction

Environmental pollution is a critical global crisis (Vuong et al., 2024), posing a significant threat to ecological balance and sustainable development (Agboola et al., 2022). With the expansion of agricultural production and the extensive application of chemical fertilizers, synthetic pesticides, and plastic mulch (Liu et al., 2020b; Zou et al., 2020), unsustainable agricultural development has led to a series of environmental challenges, including overuse of agricultural resources, environmental pollution, soil degradation, and ecological degradation (Guo et al., 2022b). Agricultural non-point source pollution has become one of the main threats to the global environment and sustainable agricultural development (Li et al., 2021). As the most populous developing country, China uses 7% of its arable land to feed 20% of the world's population (Wu et al., 2018). Over the past 30 years, the use of chemical fertilizers, pesticides, and agricultural films in China has increased two to four times, driven by the pursuit of higher crop yields and the demands of a growing population (Liu et al., 2020a). China is now the world's largest consumer of fertilizers, with an average application rate twice the recommended safety level in developed countries. However, the average utilization efficiency remains around 40% (Shuqin and Fang, 2018). Moreover, China leads the world in pesticide consumption, applying chemical pesticides at rates 2.5 to 5 times higher than the global average, yet achieving only 30% utilization efficiency (Xie and Huang, 2021). Therefore, addressing agricultural pollution from surface sources and protecting the agricultural environment have become urgent and pressing issues (Lu et al., 2023).

To further alleviate the adverse effects of agricultural pollution and enhance ecological protection, the widespread adoption of diverse green production technologies holds significant potential (Hu et al., 2023). Agricultural production involves multiple tasks, such as ploughing, transplanting, pest management, and harvesting (Deng et al., 2020). Relying on a single green production technology is insufficient to address various challenges of agricultural pollution. Therefore, it is essential to integrate multiple green production techniques into agricultural practices. The Guiding Principles for Green Agricultural Development Technologies in China (2018–2030) outline a series of green agricultural production technologies. However, the widespread adoption of these technologies faces significant barriers, including high investment costs and long return cycles (Scharfy et al., 2017). Many farmers generally lack enthusiasm for adopting diversified green production technologies, making it difficult to effectively scale up (Mao et al., 2021). For instance, coverage of green pest control for major crop diseases remains at only 41.50% (Zou et al., 2023). Studies indicate that while one-third of surveyed farmers expressed the willingness to use biopesticides, only approximately 3% actually adopted them (Pray et al., 2011). Therefore, developing evidence-based incentives to encourage farmers' adoption of diversified green production technologies has become an urgent priority. This issue is critical for effectively integrating agricultural green transition with high-quality development.

Therefore, understanding the key factors influencing farmers' decisions to adopt diversified green production technologies has become essential for advancing the green transformation of agriculture. In this context, substantial academic research has focused on the factors that influence farmers' decisions regarding green production technologies (Bunclark et al., 2018; Guo et al., 2022b). Some studies have highlighted the impact of farmers' individual and family characteristics on adopting these technologies (Sui and Gao, 2023). Individual characteristics include factors such as gender (Jacksohn et al., 2019), age (Baerenklau and Knapp, 2007), education level (Giua et al., 2022), and health status (Abadi et al., 2017). Family characteristics typically encompass family size (Ahmad and Jabeen, 2023), family income (Han et al., 2023), farm size (Cao and Zhao, 2019), and the number of family labor force (Guo et al., 2022b). However, individual and family characteristics are not the only factors influencing the adoption of green production technologies. Some studies have indicated that the adoption of green production technologies is also influenced by external factors such as government supervision, policy promotion, technical training, policy incentives, and government subsidies (Bai et al., 2022; Baloch and Thapa, 2014; Guo et al., 2022b; Luo et al., 2024).

Whether farmers adopt diversified green production technologies depends on the information they have and the information they receive from external sources. In the context of digital transformation, the internet serves as a critical tool for information acquisition, playing a key role in overcoming information barriers and facilitating the flow of knowledge (Wu et al., 2023). In recent years, researchers have increasingly focused on the impact of IU on farmers' adoption of green production technologies (Abdon and Raab, 2005; Zhao et al., 2022). However, existing research has not reached a consensus on this issue. Studies have shown that IU exerts significant impacts on the reduction in fertilizer application rates, the adoption of green fertilization technologies, integrated pest management, and the intensity of agricultural carbon emission reduction (Chen et al., 2024; Weng et al., 2023; Yuan et al., 2021). For example, Chen et al. (2022) found that accessing agricultural production information through the internet encourages farmers to adopt straw-returning technology. Zhou et al. (2023) employed a hybrid processing model under combined estimation conditions and found that IU significantly promotes the adoption of low-carbon farming technologies. Weng et al. (2023) found that IU influenced farmers' investment in organic fertilizer by improving access to credit. However, some studies noted that farmers' adoption of green production technology did not change significantly due to IU. For instance, Ding et al. (2022) found that internet extension services did not significantly reduce nitrogen fertilizer application in wheat production. Na and Kang (2023) discovered that internet users have higher fertilizer and pesticide inputs than non-users.

In the existing research on IU and green production technologies, most scholars have examined the impact of IU on adoption one or more green production technologies. However, empirical evidence regarding the impact of IU on farmers' DIGPTA remains limited. Specifically, the mechanisms by which IU influences farmers' DIGPTA are unclear. Addressing this gap is essential for promoting the widespread adoption of various agricultural green production technologies, facilitating green transformation in farming practices, and achieving sustainable agricultural development.

In summary, this paper empirically analyzes the influence of IU on farmers' DIGPTA and its mechanism of action. Drawing on data from the China Land Economy Survey (CLES) conducted between 2020 and 2022, the study employs a Tobit model. This study makes several unique contributions compared to existing research: (1) It not only investigates whether farmers adopt specific green production technologies, but also develops an index system to assess farmers' DIGPTA across the pre-production, production, and post-production stages. (2) Existing studies have primarily utilized simple regression models to confirm the impact of IU on green production behavior. For instance, Zhao et al. (2021) employed the Probit model to analyze the impact of IU on fertilizer reduction technologies, while Ma et al. (2022b) used the ordered Probit model to explore how IU affects farmers' DIGPTA. However, the endogeneity of farmers' decision-making is often neglected. Therefore, this paper addresses the potential endogeneity between the two variables and employs the IV-Tobit model to introduce instrumental variables, effectively solving this issue. (3) Existing research has largely overlooked the mechanisms through which the internet influences farmers' DIGPTA. This paper utilizes an intermediary effect model to further analyze how decision-making preferences, environmental awareness, and diversification risk perception influence farmers' DIGPTA, thereby offering more targeted suggestions to promote farmers' DIGPTA.

The remainder of this study is organized as follows. "Theoretical analysis and research hypothesis" presents the theoretical analysis and hypotheses. "Data, variables, and methods" covers the data sources, variables, and models. "Result analysis" reports and analyzes the empirical results. "Discussion" discusses the implications of the findings. Finally, "Conclusions and implications" summarizes the research and discusses the policy implications.

Theoretical analysis and research hypothesis

Impact of IU on farmers' DIGPTA. According to the economic man hypothesis, farmers adopt diversified agricultural green production technologies to maximize their benefits by weighing the associated costs and benefits before making informed decisions. If the benefits of adopting such technologies outweigh their costs, farmers are more likely to adopt them; conversely, if the costs outweigh the benefits, farmers are less inclined to adopt them. Information plays a crucial role in farmers' decision-making processes. However, farmers face several informational barriers when adopting diversified green production technologies (Zheng et al., 2022). On the one hand, farmers exhibit inertia due to uncertainty regarding various green production technologies available and their dependence on existing production methods, which hampers farmers' DIGPTA (Conti et al., 2021; Huang et al., 2020). In order to transition from an initial, inefficient state to a Pareto Optimal state, farmers must assess whether the proposed changes offer an improvement, a disadvantage, or a neutral shift compared to their current situation (Ananda and Herath, 2003). However, farmers often struggle to predict the benefits of adopting diversified green production technologies, given their varying levels of knowledge and other constraints (Morris et al., 2017). Faced with uncertain returns and increasing sunk costs, farmers stick to familiar production methods, further reinforcing inertia in decision-making (Guo et al., 2022a). Additionally, incomplete and asymmetric information acts as a significant barrier to farmers' adoption of diversified green production technologies. The absence of information regarding benefits or proper utilization of green production technologies complicates farmers' understanding of diversified technologies' costs, benefits, and applicability. This informational asymmetry is not solely a result of farmers' cognitive limitations, but is also exacerbated by the absence of adequate information in the market economy, contributing to the lemon market effect (Johnson, 2024; Ren et al., 2022; Su et al., 2022).

IU offers an effective solution to overcoming barriers to adopting diverse green production technologies. Firstly, IU enhances farmers' access to information channels (Deng et al., 2019; Zheng et al., 2021), strengthens the reliability of their information, significantly reduces uncertainty in decision-making, and improves the rationality of their decisions (Chen et al., 2022; Lioutas et al., 2021). Farmers can obtain extensive information on green production technologies via the internet, including images, short videos, and online case studies (Raj et al., 2021). This helps them better understand the benefits of diversifying green production technologies and move away from inertial decision-making, ensuring more rational decision-making outcomes. Secondly, as a medium for information dissemination, the internet breaks down barriers to information access, improves resource availability, and mitigates information asymmetry (Khan et al., 2022; Nie et al., 2021). In rural China, social networks are built on kinship and geography, and information transfer within groups tends to follow an uneven pattern. Unlike traditional information channels, the internet provides publicly accessible information, allowing farmers to obtain market insights such as agricultural product details and green production technology services through online searches, agricultural department websites, and agricultural service apps (Fabregas et al., 2019). Compared with traditional ways of obtaining information, the internet offers a more convenient and cost-effective solution, helping farmers in remote areas overcome challenges in accessing timely and comprehensive information due to geographical constraints or transportation difficulties (He et al., 2022). Thirdly, online platforms offer farmers access to training and opportunities for interaction with agricultural technology extension workers, experts, and other professionals (Kelly et al., 2017). The internet provides farmers with learning opportunities through online training programs and apps, enabling them to quickly acquire and understand new technologies. This helps improve their knowledge and reduces barriers to technology adoption caused by limited expertise. Overall, the internet is crucial in reducing information asymmetry, enhancing access to knowledge, changing habitual decision-making, and improving agricultural efficiency. These factors enable farmers to adopt diverse green production technologies and promote their broader application. Based on this premise, this paper proposes Hypothesis 1:

H1: IU can promote farmers' DIGPTA.

Mechanism of the impact of IU on farmers' DIGPTA

IU and farmers' DIGPTA: the mediating effect of decision-making preferences. Adopting diversified green production technologies in agriculture requires substantial initial investment, with benefits typically accruing over an extended period. In China's traditional small-scale peasant economy, farmers often favor short-term gains over long-term benefits, making them reluctant to adopt diversified green production technologies perceived as unprofitable in the short term (Du et al., 2023). Income uncertainty is a critical factor shaping farmers' tendency toward short-term decision-making (Mao et al., 2021). However, IU can play a pivotal role in promoting DIGPTA by shaping farmers' decision-making preferences. On the one hand, the internet serves as an essential medium for disseminating information, enabling farmers to understand the advantages of DIGPTA more comprehensively (Huang et al., 2022). By addressing decision-making biases caused by information gaps, IU can help overcome farmers' tendency to prioritize short-term benefits, facilitating a shift toward long-term decision-making. On the other hand, IU can employ digital platforms to broaden sales channels, facilitate precise matchmaking with consumers (Ji et al., 2023; Liu et al., 2022), stabilize clientele, and address the challenges of selling green agricultural products (Sher et al., 2019), thereby further reducing the market risks associated with green agricultural products. Farmers are more likely to make rational long-term decisions with a clearer understanding of market dynamics. Farmers with long-term decision-making preferences tend to focus more on technology sustainability and future returns, making them more likely to adopt a broader range of green production technologies. Therefore, this paper proposes Hypothesis 2:

H2: IU further enhances farmers' DIGPTA by promoting their long-term decision-making preferences.

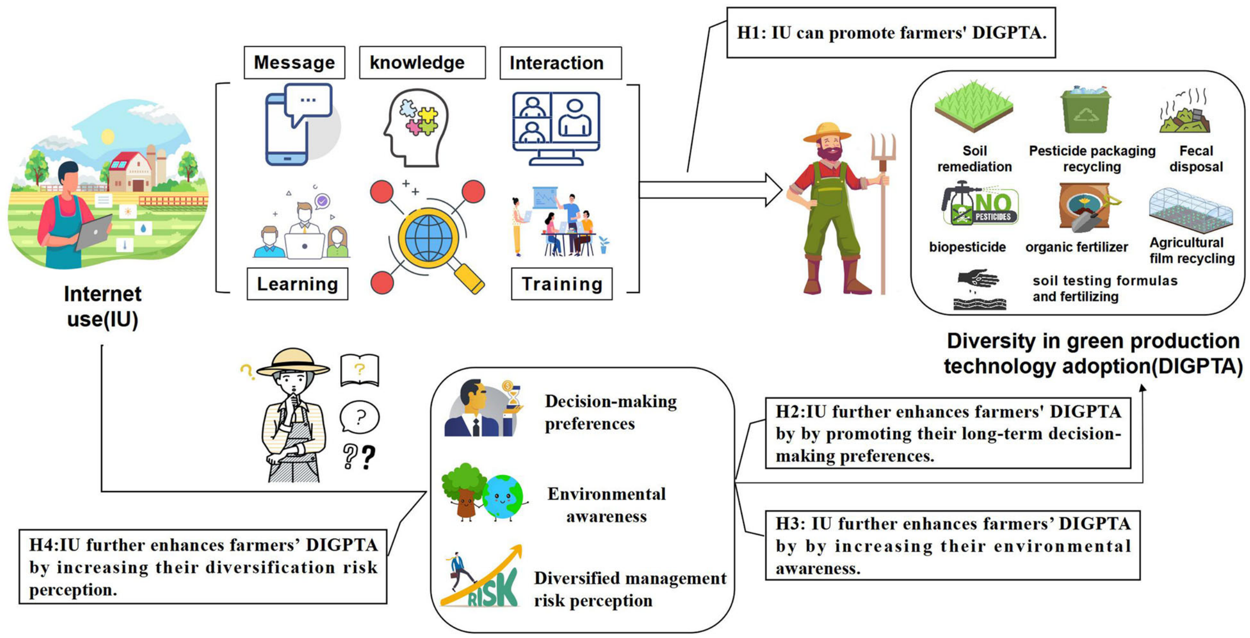

Fig. 1 Theoretical analysis frame diagram.

IU and farmers' DIGPTA: the mediating effect of environmental awareness. As a new communication medium, the internet's information transfer model overcomes the limitations of one-way communication inherent in traditional media. The internet's two-way, or even multi-directional, communication features enable farmers to access environmental information and knowledge easily (Hidalgo et al., 2023). Farmers use the internet to obtain information on agricultural production, improve their environmental attitudes, raise awareness, and modify their production behaviors accordingly. At the subjective level, information on agricultural surface pollution caused by irrational agricultural production practices is widely shared on the internet in various forms, such as videos, texts, and images (Li et al., 2023; Ma et al., 2022a). This allows farmers to understand the adverse effects of traditional farming practices, deepening their emotional engagement with environmental issues. As a result, they are more inclined to develop positive attitudes toward environmental protection and are more open to adopting various green production technologies. Additionally, the internet has expanded farmers' social networks (Zhu et al., 2022), making it easier for them to exchange information about green production and encouraging the adoption of sustainable practices (Lu et al., 2024; Niu et al., 2022). This, in turn, fosters peer effects that promote DIGPTA. IU subjects farmers to greater social supervision (Xu et al., 2023), ensuring that moral public opinion promptly addresses environmentally harmful production behaviors. In other words, information dissemination via the internet cultivates farmers' intrinsic motivation for environmental protection and applies social normative pressure. This shapes their environmental awareness from subjective and objective perspectives, encouraging DIGPTA. Therefore, this paper proposes Hypothesis 3:

H3: IU further enhances farmers' DIGPTA by increasing their environmental awareness.

IU and farmers' DIGPTA: the mediating effect of diversification risk perception. Under risk and uncertainty, risk perception is an important factor influencing individual decision-making (Sproten et al., 2018). Due to information asymmetry, farmers are often biased in assessing the risks and benefits of their farming operations (Molla et al., 2020), which leads them to make decisions that may overestimate or underestimate potential risks. As an information dissemination tool, the internet provides farmers with extensive and accurate agricultural information (Zhang et al., 2016), helping them to assess diversification risks more comprehensively. Specifically, the internet has enabled farmers to access information on pest and disease control, green production techniques, and market operations (Reddy and Ankaiah, 2005). This information transparency has helped farmers break the traditional "information blockage" (Shen et al., 2022) by recognizing that diversification can effectively diversify risks and improve the stability of crop yields and economic returns (Zou et al., 2024). In addition, the internet provides farmers with modern risk management tools (Sarkar et al., 2023), which enable farmers to more rationally assess the risk diversification effects of diversification and thus change their risk perceptions of diversification. By gaining a deeper understanding of the various risks in agriculture, farmers who recognize diversification risk perception are more likely to adopt green production technologies. This helps reduce operational uncertainty and improves the stability and sustainability of their farming practices. Therefore, this paper proposes Hypothesis 4:

H4: IU further enhances farmers' DIGPTA by increasing their diversification risk perception.

In summary, IU has a significant impact on farmers' DIGPTA. Based on this, this paper constructs a framework for theoretical analysis (see Fig. 1).

Data, variables, and methods

Data Sources. This paper utilizes data from the China Land Economic Survey (CLES) conducted by Nanjing Agricultural University in Jiangsu Province (Njau, 2021). Initiated in 2020, CLES is subsequently expanded through studies in 2021 and 2022, building on the foundational research in Jiangsu Province. The data is collected using the Probability Proportional to Size (PPS) sampling method. This method involves selecting sample counties and administrative villages across 13 prefecture-level cities in Jiangsu Province, encompassing 52 administrative villages and 2600 farm households. The steps involved in the PPS sampling method are as follows: (1) Two districts and counties

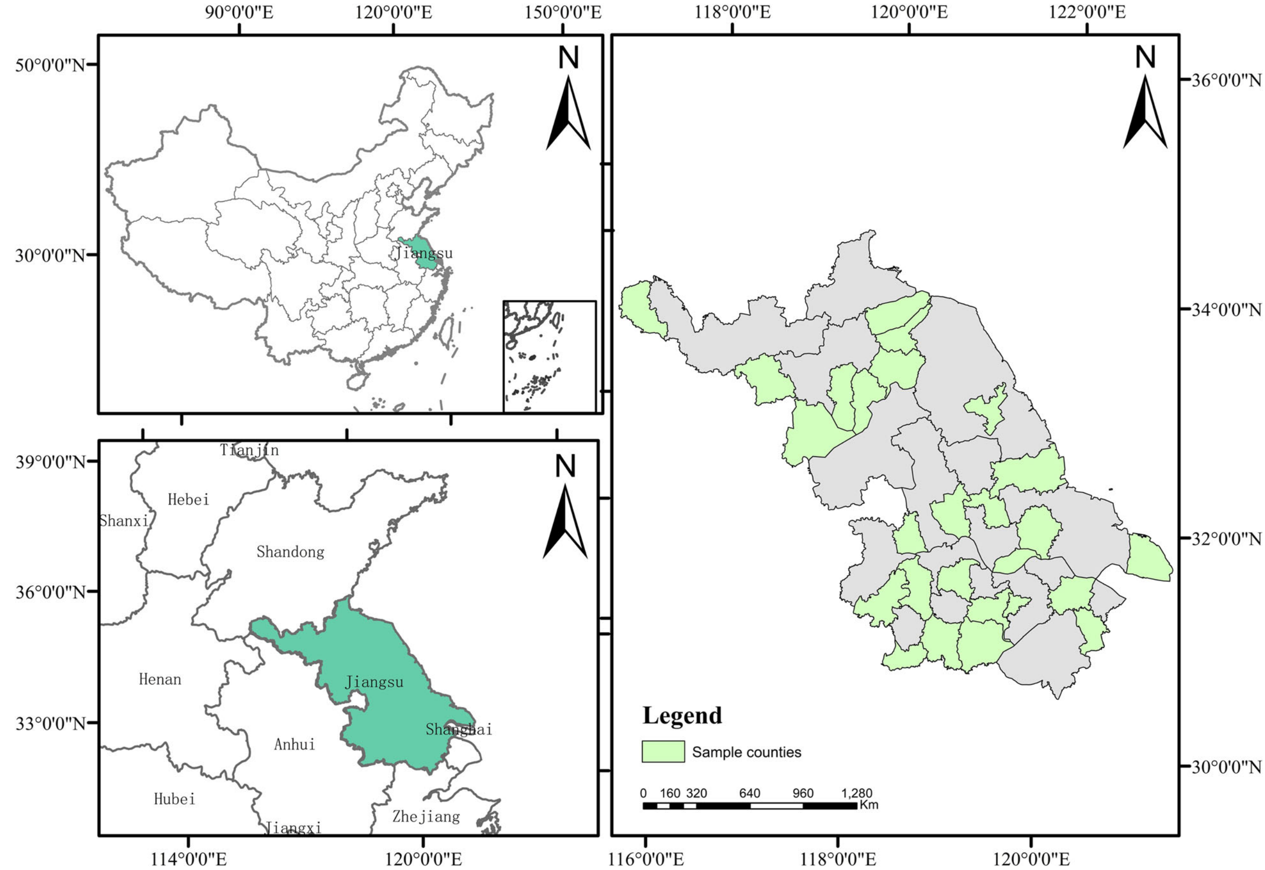

Fig. 2 Location map of the research area.

are selected from each city using unequal probability sampling based on the rural population size as reported in the 2010 census. (2) Two townships are then chosen for research in each selected district or county, again using unequal probability sampling based on the number of administrative villages. (3) Each township selects one administrative village, resulting in 52 research villages. (4) A simple random sampling method selects 50 households from each research village. The survey data spans the period from 2020 to 2022. Data screening procedures are employed to remove missing data, significant omissions, and invalid questionnaires. Ultimately, data from 6200 households are retained for analysis (see Fig. 2).

Variable selection

Dependent variables. In this study, the dependent variable is farmers' DIGPTA. Previous research on green production behavior in agriculture has predominantly focused on either the quantity of green production or the adoption of specific green technologies. However, less attention has been paid to farmers' DIGPTA. This paper selects seven indices to measure common green production technologies adopted by farmers, based on the Technical Guidelines for Agricultural Green Development (2018–2030) issued by China's Ministry of Agriculture and Rural Affairs and data from the CLES questionnaire. These indices include arable land pollution treatment and remediation technologies, agricultural film recycling, soil testing and formula fertilization, biological pesticide application, pesticide packaging recycling, organic fertilizer application, and environmentally sound livestock manure treatment. The paper adopts the livelihood diversity measurement index (Ma et al., 2020; Wu et al., 2024) to assess DIGPTA, which is based on the proportion of agricultural green production technologies utilized by farmers relative to the total number of available technologies. The value of this index directly reflects the level of farmers' DIGPTA: the higher the index, the greater the level of farmers' DIGPTA. The calculation formula is as follows:

$$G_s = \frac{A_i}{A} \tag{1}$$

A_i represents the type of agricultural green production technology adopted by the i farmer; A represents the total amount of agricultural green production technology.

Table 1 presents farmers' DIGPTA. It shows that 7.90% of farmers adopt land pollution treatment and restoration technology, 2.20% conduct soil tests for formula fertilization, and only 1.20% apply organic fertilizers in agricultural production. Biological pesticide application technology has the highest adoption rate, at 32.60%, followed by pesticide packaging recycling at 16%. Agricultural film recycling technology and livestock manure treatment technology account for just 1.30%. These figures suggest that farmers' DIGPTA needs further improvement.

Focus variables. This study builds on the research by Zhou et al. (2023) and Zhong et al. (2023), using IU as the focus variable. Based on the questionnaire item, "If you go online, what is the main way to access the internet?", this paper determines whether farmers use the internet. If farmers select a specific internet access method, they are assigned a value of 1; otherwise, they are assigned a value of 0. "Do you have a smartphone at home?" is a substitute variable for robustness testing.

Control variables. Considering the numerous factors influencing farmers' decisions to adopt diversified green production technologies, this study controls for variables across three dimensions:

Table 1 Composition of indicators for diversity in green production technology.

Variable	Agricultural production stage	Classification	Mean	S.D.
Diversity in green production technology	Before production	Farmland pollution treatment and remediation technology	0.079	0.270
	During production	Soil testing and formula fertilization	0.022	0.147
	During production	Application of organic fertilizer	0.012	0.109
	During production	Biological pesticide application	0.326	0.469
	After production	Recycling of pesticide packaging	0.160	0.367
	After production	Agricultural film recycling	0.015	0.120
	After production	Livestock waste disposal	0.013	0.115

Table 2 Variable definition and descriptive statistics.

Variables	Definition	Mean	S.D.
Technology diversity	Agricultural green production Diversity index (%)	9.187	12.895
Internet use	Does the farmer's household have internet access devices? (1=Yes; 0=No)	0.463	0.499
Head age	Age of the household decision-maker	61.590	10.750
Head gender	Whether the household decision-maker is male? (1=Yes; 0=No)	0.841	0.365
Head education	Does the household decision-maker receive education at the high school level or above? (1=Yes; 0=No)	0.188	0.391
Head health	Whether the household decision-maker is in good health? (1=Yes; 0=No)	0.731	0.443
Head job	Whether the household decision-maker is engaged in agricultural production? (1=Yes; 0=No)	0.632	0.482
Family education	The percentage of individuals in the household who have received education at high school level or above (%).	21.355	23.648
Family health	The percentage of individuals in good health within the total household population (%).	88.805	23.165
Family income	Total household income (10^4 yuan)	17.362	31.874
Family burden	The percentage of elderly and children in the total household population (%)	29.524	31.218
Family farm labor	The percentage of individuals engaged in farming within the total household population (%)	29.524	31.218
Family land size	Managing land area of rural households (mu)	6.544	23.573
Family party	Is there a party member in the household? (1=Yes; 0=No)	0.303	0.460
Village terrain	Whether the village is located in a plain area? (1=Yes; 0=No)	0.487	0.500
Distance	The distance from the village committee to the county town.	8.104	11.027
Decision-making preference	For investment activities, which situation do you prefer: 0=Only focus on immediate returns; 1=Consider both immediate and future returns	0.540	0.498
Environmental awareness	Your assessment of your own environmental behavior: 1=Not environmentally friendly; 2=Average; 3=Very environmentally friendly	2.622	0.522
Diversification risk perception	In general, do you believe that cultivating (operating) multiple crops carries less risk than cultivating (operating) a single crop: 1=Yes; 0=No	0.405	0.491

individual characteristics, household characteristics, and village characteristics (Zhang et al., 2025; Zheng et al., 2022; Zhou et al., 2023). Based on the studies by Hong et al. (2020) and Boz (2016), individual characteristics include gender, age, education level, health status, and employment status. Family characteristics, as identified by Niu et al. (2022) and Zhang et al. (2024), encompass the average family education level, family income, family health status, family burden, the proportion of family members involved in agriculture, land size, and whether there are party members in the family. Village characteristics, including topography and distance from the county seat, are measured by the village committee (Fenni et al., 2019; Xie and Gao, 2023). Finally, urban and temporal dummy variables are included to mitigate the impact of regional and temporal differences on the regression results.

Mediating variables. Based on the theoretical analysis of how IU promotes farmers' DIGPTA, this paper selects three mediating variables: decision preference, environmental protection awareness, and diversification risk perception. Drawing from the studies of Xu et al. (2024) and Zhu et al. (2024), the question "Which investment would you prefer from the following options?" is used to measure decision-making preference; "How do you assess your environmental behavior?" is used to measure environmental awareness; and "Do you consider that growing or operating a variety of crops is generally less risky than focusing on one crop?" is used to measure farmers' diversification risk perception. The definitions of specific variables are shown in Table 2.

As shown in Table 2, farmers' DIGPTA is only 9.19%, farmers' current adoption of green production technology remains relatively limited and that DIGPTA is insufficient. Regarding IU, only 46.30% of rural farmers have access to the internet, highlighting the still relatively low IU rate in rural areas. In terms of individual characteristics, the average age of household heads is 61.59 years, with the majority (84.10%) being male, and 73.10% reporting good health. Household education levels are generally low, with only 18.80% having a high school education or above, and 63.20% engaged in agricultural production. As for family characteristics, 21.36% of family members have a high school education or above, and 88.81% are in good health. The family burden accounts for 40.92%, while family labor constitutes 29.52%. The average family income is 173,620 yuan, with an average landholding of 6.54 mu, and 30.30% of families include party members. Concerning village characteristics, 48.70% of farmers live in plain areas, with the average distance from the village committee to the county seat being 8.10 km.

Research methods

Model setting. The DIGPTA index ranges from 0 to 100, so it is regarded as a typical truncation at both ends, that is, the explanatory variables are limited. Although ordinary least squares regression is commonly used for coefficient estimation, applying it to truncated dependent variables can lead to biased and inconsistent parameter estimates. To cope with this problem, Tobin (1958) proposed the truncated regression model, which uses maximum likelihood instead of ordinary least squares and is often referred to as the Tobit model. A key feature of the Tobit model is that the dependent variable is truncated in terms of the values it takes and, therefore, observed in a restricted manner. Theoretically, the maximum likelihood method can also be considered a coefficient regression method for estimating the regression parameters in a model. Currently, many economists have adopted the Tobit model to analyze various problems. This study, therefore, employs the Tobit model to examine the impact of IU on farmers' DIGPTA. The specific model setup is as follows:

The probability distribution of the Tobit model is as follows:

$$P(Y_i=0)=P(Y_i^*\leq 0)=P\left(\frac{Y_i^*-\beta X_i}{\sigma}\leq\frac{0-\beta X_i}{\sigma}\right)=\varphi\left(-\frac{\beta X_i}{\sigma}\right)=1-\varphi\left(\frac{\beta X_i}{\sigma}\right) \tag{2}$$

$$P(Y_i)=P(Y_i^*)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(Y_i-\beta X_i)^2}{2\sigma^2}} \tag{3}$$

The following are the maximum likelihood estimates of the Tobit model:

$$L=\prod\nolimits_{y_i>0}\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(y_i-\beta x_i)^2}{2\sigma^2}}\prod\nolimits_{y_i=0}1-\varphi\left(\frac{\beta x_i}{\sigma}\right) \tag{4}$$

$$\ln L=\sum\nolimits_{y_i>0}-\frac{1}{2}\left(\ln(2\pi)+\ln\sigma^2+\frac{(y_i-\beta x_i)^2}{2\sigma^2}+\sum\nolimits_{y_i=0}\ln\left(1-\varphi\frac{\beta x_i}{\sigma}\right)\right) \tag{5}$$

This paper selects the standard Tobit model for estimation and sets the left-end cutoff point to 0. The regression model is established as follows:

$$AGPD_i^*=\alpha Internet_i+\beta_1 X_i+\varepsilon_i \tag{6}$$

$$AGPD_i=\begin{cases}0, & otherwise\\ AGPD_i^*, & 0\leq AGPD_i^*\leq 100\end{cases} \tag{7}$$

Where $AGPD_i$ is the DIGPTA index of the i th farmer; α andβ_1 are the parameters to be estimated ; $Internet_i$ indicates whether to use the internet;X_i is the control variable that affects farmers' DIGPTA index ; ε_i is a randomized perturbation term.

Model endogeneity. Indeed, there is reverse causality between IU and farmers' DIGPTA. As farmers adopt a range of green production technologies, they may increase their IU to access additional technical information. Moreover, the model may omit variables correlated with other explanatory variables due to the challenge of controlling for all factors influencing farmers' DIGPTA. Consequently, this paper adopts the instrumental variable approach (IV-Tobit) to address model endogeneity. According to peer effect theory, individual choices are influenced by the decisions of others within their social networks (Zhuang et al., 2021). To reduce the decision-making risk associated with incomplete information, people tend to learn from others' decisions or behaviors to reduce uncertainty (Xu et al., 2020). Building on this theory, this study follows the methodology of Deng et al. (2021) and Yu et al. (2023), selecting "the proportion of IU among other farmers in the village, excluding the local household" as the instrumental variable for IU. An increase in village-wide IU will likely lead to a higher propensity for individuals in the vicinity to use the internet, thus influencing their decisions regarding IU by the relevant conditions. Furthermore, since the IU data are collected at the village level, they generally do not directly impact farmers' DIGPTA, thus meeting the homogeneity condition.

Intermediary effect model. In this paper, following the stepwise regression method proposed by Baron and Kenny (1986), the following model is constructed to test the mediation effect:

$$AGPD_i=\lambda_0+\lambda_1 Internet_i+\lambda_2 Controls_i+\eta_i \tag{8}$$

$$Media_i=\theta_0+\theta_1 Internet_i+\theta_2 Controls_i+\varepsilon_i \tag{9}$$

$$AGPD_i=\delta_0+\delta_1 Internet_i+\delta_2 Media_i+\delta_3 Controls_i+\upsilon_i \tag{10}$$

Where $AGPD_i$ represents the DIGPTA index of the i th farmer, $Internet_i$ indicates whether the i th farmer uses the internet ; $Media_i$ stands for decision-making preference, environmental awareness, and diversification risk perception;$Controls_i$ and represents a set of control variables. Equation (8) examines the overall effect, Eq. (9) focuses on the intermediary effect, and Eq. (10) incorporates both core explanatory variables and intermediary variables into the model to analyze their combined impact on farmers' DIGPTA. The mediating effect is the product of coefficients θ_0 andδ_2.

Result analysis

Baseline regression. The estimated results of the model are presented in Table 3. Models 1 through 5 show the sequential model estimation results, which progressively incorporate the province dummy variable, time dummy variable, personal characteristics of the household decision-maker, family characteristics, and village characteristics. Model 6 presents the marginal effect calculated from the estimation results of Model 5. The findings indicate that the Wald chi-square test for all six models reaches the 1% significance level, confirming the validity of the regression analysis. Furthermore, the coefficient for IU is significantly positive in all models (from Model 1 to Model 6). The marginal effect results from Model 6 suggest that IU positively influences farmers' DIGPTA at the 1% significance level. As IU increases by one unit, the farmers' DIGPTA index rises by 53.10%.

From individual characteristics, age, gender, and health status significantly influence DIGPTA. The age of household decision-makers is negatively associated with the farmers' DIGPTA index (at the 1% significance level). The gender of the household decision-maker positively influences farmers' DIGPTA index (at the 1% significance level), suggesting that men are more likely than women to adopt a broader range of green production technologies. The health status of household decision-makers also positively affects farmers' DIGPTA (at the 10% significance level), indicating that healthier farmers are more inclined to adopt various green production technologies. At the family level, the average household education level (at the 10% significance level), household income (at the 1% significance level), household burden (at the 1% significance level), the proportion of household members engaged in agriculture (at the 1% significance level), and land scale (at the 1% significance level) all significantly influence farmers' DIGPTA. Additionally, the distance from the village to the county seat negatively influences farmers' DIGPTA at the 5% significance level, suggesting that greater distance from the county seat hinders the adoption of diversified green production technologies.

Endogeneity test. Table 4 presents the results of the endogeneity test using the IV-Tobit model, with the instrumental variable being the "percentage of IU in the village among farmers other than the local household." In the first stage, the coefficient of this

Table 3 Baseline regression.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Internet use	1.341*** (4.089)	1.867*** (5.941)	1.144*** (3.346)	0.933*** (2.720)	0.939*** (2.738)	0.531*** (2.737)
Head age			−0.128*** (−7.353)	−0.090*** (−4.637)	−0.090*** (−4.612)	−0.051*** (−4.608)
Head gender			1.564*** (3.651)	1.158*** (2.719)	1.150*** (2.700)	0.650*** (2.699)
Head education			−0.973** (−2.363)	−0.617 (−1.278)	−0.597 (−1.236)	−0.338 (−1.236)
Head health			1.257*** (3.487)	0.788* (1.956)	0.771* (1.914)	0.436* (1.914)
Head job			1.867*** (5.293)	0.387 (0.986)	0.367 (0.935)	0.207 (0.935)
Family education				−0.015* (−1.817)	−0.015* (−1.817)	−0.009* (−1.817)
Family income				0.006*** (4.352)	0.006*** (4.294)	0.003*** (4.293)
Family burden				−0.018*** (−2.938)	−0.018*** (−2.935)	−0.010*** (−2.934)
Family farm labor				0.043*** (7.541)	0.043*** (7.507)	0.024*** (7.493)
Family health				0.010 (1.240)	0.009 (1.211)	0.005 (1.211)
Family land size				0.039*** (5.941)	0.039*** (5.955)	0.022*** (5.958)
Family party				0.279 (0.802)	0.308 (0.885)	0.174 (0.885)
Village terrain					0.551 (0.887)	0.311 (0.887)
Distance					−0.074** (−2.305)	−0.042** (−2.304)
Constant	8.566*** (38.400)	2.193*** (3.843)	6.986*** (5.529)	5.096*** (3.693)	5.090*** (3.689)	
City dummies	No	Yes	Yes	Yes	Yes	Yes
Year dummies	No	Yes	Yes	Yes	Yes	Yes
ll	−24,641.161	−24,275.869	−24,232.780	−24,167.757	−24,164.892	−24,164.892
chi2	16.695***	747.279***	833.456***	963.502***	969.233***	969.233***
N	6200	6200	6200	6200	6200	6200

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

Table 4 Endogeneity test.

	Model (1)	Model (2)
	First stage	Second stage
Peer	0.487*** (8.801)	
Internet use		24.568*** (3.161)
Control variables	YES	YES
City dummies	YES	YES
Year dummies	YES	YES
F statistics	62.002***	
Wald test of exogeneity (chi2)		9.940**
N	6200	6200

t statistics in parentheses; **$p < 0.05$, ***$p < 0.01$.

instrumental variable is significant at the 1% level. Additionally, the F-statistic from the weak instrument test exceeds the critical value of 10, thereby rejecting the hypothesis of a weak instrument and indicating that it is not weak. The second stage of the Wald test (chi2) rejected the hypothesis of "exogenous variables in the model" at the 5% significance level, showing that IU is identified as an endogenous variable, underscoring the importance of using instrumental variables to mitigate the endogeneity problem. Furthermore, results from this method show that the direction of the coefficients in the model is consistent with those from the baseline regression, further supporting Hypothesis H1.

Robustness test. Four distinct testing methods are employed to assess the robustness of the findings, with the results presented in Table 5. In Model (1), the dependent variable is substituted, as previous studies typically measure green production behavior by adopting green technologies. A higher number of adopted technologies generally reflects greater farmers' DIGPTA. Therefore, this paper replaces the explanatory variable with the total count of adopted green technologies. In Model (2), smartphone ownership is used as a replacement for the independent variable; in Model (3), regression analysis is conducted using a subsample; and in Model (4), the IV-Reg model is applied. From the regression results in Table 5, it can be seen that IU has a significant positive impact on farmers' DIGPTA, whether in terms of replacement variables, sample size, or model, which indicates the results' robustness.

Heterogeneity analysis. Table 6 presents the results of the heterogeneity analysis based on generational differences. Following the classification proposed by Xie and Huang (2021), farmers born after 1970 are categorized as new-generation farmers, while those born before 1970 are classified as old-generation farmers. Models 1 and 2 in Table 6 use the Tobit baseline model, while Models 3 and 4 apply IV-Tobit models with instrumental variables. The SUEST test is used to assess whether there are significant differences in coefficients between the two groups. The p-values from the SUEST test are 0.062 and 0.071, both significant at the 10% level, indicating a substantial coefficient difference between the two groups. This suggests generational differences in the impact of IU on farmers' DIGPTA. In the baseline model, IU significantly influences DIGPTA among new-generation farmers, while it has no significant effect on old-generation farmers. After addressing endogeneity with the IV-Tobit model, the results reveal that IU continues to exert a greater impact on farmers' DIGPTA among new-generation farmers than old-generation farmers.

Intermediate effect test. Findings from the aforementioned study conclusively demonstrate that IU significantly and positively impacts farmers' DIGPTA. However, the underlying mechanism remains unclear and requires further investigation. This study first examines the role of decision-making preferences in mediating IU's impact on farmers' DIGPTA, with results presented in Table 7. Column (1) of Table 7 presents the baseline model, evaluating the relationship between IU and farmers' DIGPTA. Column (2) examines IU's impact on farmers' decision-making preferences, indicating a significant increase in such preferences due to IU. Column (3) demonstrates that when both IU and decision-making preferences are included in the regression equation assessing farmers' DIGPTA, both variables remain positively correlated with DIGPTA. This suggests that decision-

Table 5 Robustness analysis.

	Model (1) Substitute for the dependent variable	Model (2) Substitute for the independent variable	Model (3) Subsample regression: (year = 2020)	Model (4) Substitute model: IV-Reg
Internet use	0.066*** (2.738)		1.281*** (2.605)	11.280*** (3.419)
Smartphone		2.085*** (4.368)		
Control variables	YES	YES	YES	YES
City dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
ll	−7677.480	−24,159.113	−9956.952	
chi2	969.233***	980.790***	417.255***	920.149***
N	6200	6200	2619	6200

t statistics in parentheses; ***$p < 0.01$.

Table 6 Heterogeneity analysis.

	(1) New-generation	(2) Old-generation	(3) New-generation	(4) Old-generation
Internet use	2.492*** (2.679)	0.562 (1.506)	55.341*** (2.755)	17.101* (1.835)
Control variables	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
ll	−4080.413	−20,058.975	−2909.320	−14,280.492
chi2	241.608***	764.672***	160.147***	705.599***
N	1043	5157	1043	5157
SUEST test	3.472* (0.062)		3.270* (0.071)	

t statistics in parentheses; *$p < 0.10$, ***$p < 0.01$.

Table 7 Analysis of the intermediary mechanism of decision-making preferences.

	Mechanism 1: Internet use → Decision-making preference → Technology diversity		
	(1) Technology diversity	(2) Decision-making preference	(3) Technology diversity
Internet use	0.939*** (2.738)	0.184*** (5.024)	0.893*** (2.599)
Decision-making preference			0.647** (2.065)
Control variables	YES	YES	YES
City dummies	YES	YES	YES
Year dummies	YES	YES	YES
chi2	969.233***	379.522***	973.494***
N	6200	6200	6200

t statistics in parentheses; **$p < 0.05$, ***$p < 0.01$.

making preferences serve as a mediator between IU and farmers' DIGPTA. Specifically, IU's coefficient for farmers' DIGPTA decreases from 0.939 to 0.893 after incorporating mediator variables. Moreover, the proportion of the mediation effect amounts to 11.90%, indicating that 11.90% of IU's influence on farmers' DIGPTA can be attributed to its impact on long-term decision-making preferences. Thus, Hypothesis 2 is supported. A plausible explanation is that IU provides farmers with abundant and diverse information channels, facilitating easier access to the latest green production technologies and related information (Zhang et al., 2016). Farmers are exposed to numerous new technologies and methods through long-term IU, gradually shaping decision-making preferences toward adopting a broader range of green production technologies.

Secondly, this paper examines the mediating effect of environmental awareness on IU concerning farmers' DIGPTA, with the results presented in Table 8. According to Table 8, column (1) is a baseline model to test the effect of IU on farmers' DIGPTA, and column (2) investigates the impact of IU on farmers' environmental awareness. Column (3) incorporates IU and environmental awareness into the regression equation for farmers' DIGPTA. Both factors are positively correlated with farmers' DIGPTA. This suggests that environmental awareness is an intermediary between IU and farmers' DIGPTA. Specifically, after introducing the mediating variables into the model, the impact coefficient of IU on farmers' DIGPTA decreased from 0.939 to 0.871, and the mediating effect accounted for 6.79%, that is, 6.79% of the impact of IU on farmers' DIGPTA is achieved by affecting farmers' environmental protection cognition. Therefore, Hypothesis 3 is examined. The internet provides extensive knowledge about environmental protection. Simultaneously, news and reports on environmental pollution and ecological destruction circulated via the internet can heighten farmers' awareness of environmental issues (Xu et al., 2023). Through the internet,

Table 8 Analysis of the intermediary mechanism of environmental awareness.

	Mechanism 2: Internet use → Environmental awareness → Technology diversity		
	(1) Technology diversity	(2) Environmental awareness	(3) Technology diversity
Internet use	0.939*** (2.738)	0.060*** (4.118)	0.871** (2.539)
Environmental awareness			1.131*** (3.803)
Control variables	YES	YES	YES
City dummies	YES	YES	YES
Year dummies	YES	YES	YES
chi2	969.233***	326.891***	983.676***
N	6200	6200	6200

t statistics in parentheses; ** $p < 0.05$, *** $p < 0.01$.

Table 9 Analysis of the intermediary mechanism of diversification risk perception.

	Mechanism 3: Internet use →Diversification risk perception → Technology diversity		
	(1) Technology diversity	(2) Diversification risk perception	(3) Technology diversity
Internet use	0.939*** (2.738)	0.243*** (6.570)	0.876** (2.546)
Diversification risk perception			0.693** (2.156)
Control variables	YES	YES	YES
City dummies	YES	YES	YES
Year dummies	YES	YES	YES
chi2	969.233***	502.221***	973.880***
N	6200	6200	6200

t statistics in parentheses; ** $p < 0.05$, *** $p < 0.01$.

farmers gain insights into the significance of environmental protection, and the benefits of green production technology, and recognize the necessity of adopting such technology to mitigate environmental degradation. Consequently, this knowledge enhances farmers' environmental awareness and consequently fosters their willingness to embrace diverse green production technologies.

Additionally, the mediating effect of diversification risk perception in IU on farmers' DIGPTA is tested and the results are shown in Table 9. Table 9 illustrates the baseline model in column (1), which assesses the impact of IU on farmers' DIGPTA. Column (2) explores the influence of IU on farmers' diversification risk perception, revealing a significant enhancement in farmers' diversification risk perception due to IU. Column (3) reveals that after including IU and diversification risk perception in the regression equation for assessing farmers' DIGPTA, they positively correlate with such diversity. This suggests that diversification risk perception is an intermediary between IU and farmers' DIGPTA. Specifically, after introducing the mediating variable into the model, the coefficient representing the influence of IU on farmers' DIGPTA decreased from 0.939 to 0.876. The mediating effect accounts for 16.84%, suggesting that 16.84% of the influence of IU on farmers' DIGPTA is explained by its impact on farmers' diversification risk perception. Hypothesis 4 is supported. A reasonable explanation is that diversified planting is an effective means for farmers to reduce risks (Chen et al., 2023). IU can affect farmers' diversification risk perception of different agricultural management methods. Farmers who prefer agricultural diversification and believe that diversification risks are low tend to have higher risk perceptions (Kiani et al., 2021). However, when farmers operate multiple crops, they may face the risk of managing multiple crops, and farmers need to adopt more green production technologies to cope with the risks of agricultural diversification (Fang et al., 2021). As farmers recognize the multifaceted risks involved in agricultural operations, heightened diversification risk perception encourages them to enhance DIGPTA.

Discussion

Encouraging farmers in rural areas of developing countries to adopt diverse green production technologies is challenging due to limited awareness. This study finds that farmers' DIGPTA in China is only 9.19%, indicating that the current adoption of green production technologies is relatively homogeneous, and DIGPTA remains insufficient. Despite various policies and initiatives promoting green technology diffusion, China's adoption rate falls short of expectations. This study shows that IU significantly enhances farmers' DIGPTA, aligning with the findings of Ma et al. (2022a) and Zhao et al. (2021). In the global push for environmentally sustainable development, the internet, a key component of information and communication technologies, is crucial in increasing DIGPTA in rural areas. As an essential information access channel, the internet enables farmers to access information on various green production technologies quickly, helping them understand the benefits of adopting diversified green production methods (Mapiye et al., 2023), such as improving production efficiency and reducing environmental impacts (Yang et al., 2024). This increased awareness motivates farmers to adopt these technologies to maximize utility. Furthermore, the internet fosters information sharing and interaction among farmers. Farmers can exchange experiences and success stories through online platforms, overcoming geographical and social barriers (Bowen and Morris, 2019). This mechanism enriches farmers' knowledge and builds trust and recognition of diversified green production technologies, encouraging their adoption. The internet also provides learning opportunities for farmers. Farmers can easily learn about new technologies through online training and application channels, improving their knowledge (Deng et al., 2024). This mitigates adoption barriers related to insufficient knowledge and increases their willingness to experiment with and apply diversified green production technologies. Therefore, hypothesis 1 is confirmed.

However, research on the mechanisms through which IU influences farmers' DIGPTA remains limited. This empirical study finds that IU can promote farmers' DIGPTA in three pathways: enhancing long-term decision-making preferences, environmental awareness, and perceptions of diversified operational risks. This study makes a significant contribution to the existing literature in this field. Further research suggests that IU has a greater impact on DIGPTA among new-generation farmers, who generally have higher education levels, greater technology acceptance, and more frequent engagement with IU (Piancharoenwong and Badir, 2024). These factors increase their likelihood of accessing and adopting information about diverse green production technologies. Moreover, the widespread use of the internet has improved information dissemination efficiency, enabling new-generation farmers to quickly understand the benefits, application cases, and policy support for adopting such technologies (Gao et al., 2020), further boosting their willingness to adopt them. In contrast, older-generation farmers may lag in their IU and lack familiarity with emerging green technologies, resulting in a lower willingness to adopt diversified green technologies.

This study has several limitations: (1) The research is confined to China, which makes the findings region-specific. Future research could examine whether these conclusions are applicable to other developing countries. (2) It is important to note that the data used in this study rely on the recollections and statements of the interviewed farmers, which may be influenced by biases such as recall bias and social desirability bias.

Conclusions and implications

Conclusions. Promoting sustainable agricultural development has become a critical issue in the context of China's "dual carbon" strategy. Advancing diversified green production technologies is a key strategy for achieving this goal. These technologies reduce agricultural carbon emissions and support low-carbon development in rural areas. They help mitigate environmental pollution from agricultural waste and chemical use while improving rural ecosystems. Additionally, the production of green agricultural products provides farmers with opportunities to enhance both productivity and income. However, ensuring farmers' DIGPTA remains an urgent challenge. As China advances its "digital countryside" initiative, the development of internet technology offers new opportunities for promoting these technologies. Using micro-survey data from the China Land Economic Survey (CLES) conducted between 2020 and 2022, this paper employs the IV-Tobit model to examine the impact of IU on farmers' DIGPTA and its causal pathways. The key findings of this study are as follows:

(1) Regarding IU, only 46.30% of farmers are internet users, indicating that the internet adoption rate in rural areas remains relatively low.

(2) A significant positive correlation exists between IU and farmers' DIGPTA, and this relationship holds after conducting robustness tests. Further heterogeneity analysis reveals that IU has a stronger impact on DIGPTA among new-generation farmers than old-generation farmers.

(3) IU can promote farmers' DIGPTA by improving their decision-making preferences, environmental awareness, and diversification risk perception.

Policy implications. Based on the above conclusions, some policy implications can be drawn: (1) Expanding internet access. The government should increase investment in rural internet infrastructure, prioritizing the expansion of coverage in less developed areas. Although most rural areas have internet access, farmers' use rates remain low. Therefore, broadband coverage should be expanded, network signals optimized, internet speeds increased, and access fees reduced. These measures will ensure stable and fast internet access for farmers, helping to bridge the "digital divide." (2) Strengthen internet literacy training. Free or low-cost digital technology training should be offered to enhance their capabilities to address the lack of IU skills in rural areas, particularly among older farmers. Through cooperatives, agricultural extension stations, and other organizations, provide targeted training on integrating green agricultural production with digital technology, helping farmers incorporate the internet into their green production practices. (3) Developing and enhancing policies. The government should introduce policies and regulations that define the internet's role in green agricultural production, outline specific application scenarios, and facilitate technology adoption. These policies should be accompanied by extensive public outreach and education efforts to help farmers understand and embrace these technologies. Regular training sessions and policy explanations will enhance farmers' knowledge of diversified green production technologies, particularly regarding the market potential and long-term benefits of green agricultural products. (4) Promoting digital agriculture platforms. Share specific environmental cases, scientific research findings, and successful practices in green agricultural technologies, encouraging farmers to actively exchange their experiences. Additionally, the government can offer financial subsidies or risk-sharing mechanisms to alleviate farmers' economic burden, boost their confidence in adopting new technologies, and promote their DIGPTA.

Data availability

Data will be made available on request.

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References

Abadi N, Gebrehiwot K, Techane A, Nerea HJ (2017) Links between biogas technology adoption and health status of households in rural Tigray, Northern Ethiopia. Energy Policy 101:284–292

Abdon BR, Raab RT (2005) Knowledge sharing and distance learning for sustainable agriculture in the Asia-Pacific region: the role of the Internet. Plant Prod Sci 8:298–307

Agboola PO, Bekun FV, Agozie DQ, Gyamfi BAJ (2022) Environmental sustainability and ecological balance dilemma: accounting for the role of institutional quality. Environ Sci Pollut Res 29:74554–74568

Ahmad M, Jabeen GJ (2023) Biogas technology adoption and household welfare perspectives for sustainable development. Energy Policy 181:113728

Ananda J, Herath G (2003) Soil erosion in developing countries: a socio-economic appraisal. J Environ Manag 68:343–353

Baerenklau KA, Knapp KC (2007) Dynamics of agricultural technology adoption: age structure, reversibility, and uncertainty. Am J Agric Econ 89:190–201

Bai J, Wang Y, Sun W (2022) Exploring the role of agricultural subsidy policies for sustainable agriculture based on Chinese agricultural big data. Sustain Energy Technol Assess 53:102473

Baloch AM, Thapa BGJ (2014) Agricultural extension in Balochistan, Pakistan: date palm farmers' access and satisfaction. J Mt Sci 11:1035–1048

Baron RM, Kenny DA (1986) The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. J Pers Soc Psychol 51:1173

Bowen R, Morris W (2019) The digital divide: implications for agribusiness and entrepreneurship. Lessons from Wales. J Rural Stud 72:75–84

Boz I (2016) Effects of environmentally friendly agricultural land protection programs: evidence from the Lake Seyfe area of Turkey. J Integr Agric 15:1903–1914

Bunclark L, Gowing J, Oughton E, Ouattara K, Ouoba S, Benao DJ (2018) Understanding farmers' decisions on adaptation to climate change: exploring adoption of water harvesting technologies in Burkina Faso. Glob Environ Change 48:243–254

Cao H, Zhao K(2019) Farmland scale and farmers' pro-environmental behavior: Verification of the inverted U hypothesis. Resour Sci 41:740–752

Chen F, Zhang C, Wang W (2022) Study on the impact of Internet use on farmers' straw returning to the field: a micro survey data from China. Sustainability 14:8917

Chen X, Xia M, Zeng D, Fan XJ (2023) Citrus specialization or crop diversification: the role of smallholder's subjective risk aversion and case evidence from Guangxi. China Horticulturae 9:627

Chen Z, Li X, Xia X (2024) The impact of internet use and cognitive conflict on farmer IPM technology adoption: evidence from China. Pest Manag Sci 80:5050–5063

Conti C, Zanello G, Hall AJ (2021) Why are agri-food systems resistant to new directions of change? A systematic review. Glob Food Security 31:100576

Deng X, Lian P, Zeng M, Xu D, Qi YJ (2021) Does farmland abandonment harm agricultural productivity in hilly and mountainous areas? evidence from China. J Land Use Sci 16:433–449

Deng X, Peng J, Wan C (2024) The impact of internet use on land productivity: evidence from china land economy survey. Land 13:262

Deng X, Xu D, Zeng M, Qi Y (2019) Does Internet use help reduce rural cropland abandonment? Evidence from China. Land Use Policy 89:104243

Deng X, Xu D, Zeng M, Qi Y (2020) Does outsourcing affect agricultural productivity of farmer households? Evidence from China. China Agric Econ Rev 12(4):673–688
Ding J, Li J, Liu J, Zhang W, Jia X (2022) ICT-based agricultural advisory services and nitrogen management practices: A case study of wheat production in China. J Integr Agric 21:1799–1811
Du F, Zhao X, Zheng J, Zhang M (2023) Can digital literacy promote green production for farmers ?— based on CLES data. World Agric 10:97–109
Fabregas R, Kremer M, Schilbach F (2019) Realizing the potential of digital development: the case of agricultural advice. Science 366:eaay3038
Fang L, Hu R, Mao H, Chen SJ (2021) How crop insurance influences agricultural green total factor productivity: evidence from Chinese farmers. J Clean Prod 321:128977
Fenni LI, Junbiao Z, Ke HE(2019) Impact of informal institutions and environmental regulations on farmers' green production behavior: based on survey data of 1105 households in Hubei Province. Resour Sci 41:1227–1239
Gao Y, Zhao D, Yu L, Yang H (2020) Influence of a new agricultural technology extension mode on farmers' technology adoption behavior in China. J Rural Stud 76:173–183
Giua C, Materia VC, Camanzi L (2022) Smart farming technologies adoption: which factors play a role in the digital transition? Technol Soc 68:101869
Guo W, Zhao W, Min MJ (2022a) Operation scale, transfer experience, and farmers' willingness toward farmland transfer-in: a case study of rice–crayfish cultivating regions in China. Sustainability 14:4081
Guo Z, Chen X, Zhang Y (2022b) Impact of environmental regulation perception on farmers' agricultural green production technology adoption: a new perspective of social capital. Technol Soc 71:102085
Han H, Zou K, Yuan Z (2023) Capital endowments and adoption of agricultural green production technologies in China: a meta-regression analysis review. Sci Total Environ 897:165175
He Y, Li K, Wang Y (2022) Crossing the digital divide: the impact of the digital economy on elderly individuals' consumption upgrade in China. Technol Soc 71:102141
Hidalgo F, Quiñones-Ruiz XF, Birkenberg A, Daum T, Bosch C, Hirsch P, Birner R (2023) Digitalization, sustainability, and coffee. Opportunities and challenges for agricultural development. Agric Syst 208:103660
Hong W, Luo B, Hu X (2020) Land titling, land reallocation experience, and investment incentives: evidence from rural China. Land Use Policy 90:104271
Hu Y, Koondhar MA, Kong R (2023) From traditional to smart: exploring the effects of smart agriculture on green production technology diversity in family farms. Agriculture 13:1236
Huang Y, Luo X, Tang L, Yu WJ (2020) The power of habit: does production experience lead to pesticide overuse? Environ Sci Pollut Res 27:25287–96
Huang Z, Zhuang J, Xiao S (2022) Impact of mobile internet application on farmers' adoption and development of green technology. Sustainability 14:16745
Jacksohn A, Grösche P, Rehdanz K, Schröder C (2019) Drivers of renewable technology adoption in the household sector. Energy Econ 81:216–226
Ji X, Xu J, Zhang H (2023) Environmental effects of rural e-commerce: a case study of chemical fertilizer reduction in China. J Environ Manag 326:116713
Johnson D (2024) Food security, the agriculture value chain, and digital transformation: the case of Jamaica's agricultural business information system (ABIS). Technol Soc 77:102523
Kelly N, Bennett JM, Starasts AJ (2017) Networked learning for agricultural extension: a framework for analysis and two cases. J Agric Educ Ext 23:399–414
Khan N, Ray RL, Zhang S, Osabuohien E, Ihtisham M (2022) Influence of mobile phone and internet technology on income of rural farmers: evidence from Khyber Pakhtunkhwa Province, Pakistan. Technol Soc 68:101866
Kiani AK, Sardar A, Khan WU, He Y, Bilgic A, Kuslu Y, Raja MAZJ (2021) Role of agricultural diversification in improving resilience to climate change: an empirical analysis with Gaussian paradigm. Sustainability 13:9539
Li Z, Huang Y, Yang Y, Lai X (2023) Can TikTok be a good way to extend the adoption of green control techniques? Evidence from rural China. Asian J Technol Innov 31:711–728
Li Z, Sarwar S, Jin TJ (2021) Spatiotemporal evolution and improvement potential of agricultural eco-efficiency in Jiangsu Province. Front Energy Res 9:746405
Lioutas ED, Charatsari C, De Rosa M (2021) Digitalization of agriculture: a way to solve the food problem or a trolley dilemma? Technol Soc 67:101744
Liu W, Wei S, Wang S, Lim MK, Wang Y (2022) Problem identification model of agricultural precision management based on smart supply chains: an exploratory study from China. J Clean Prod 352:131622
Liu Y, Sun D, Wang H, Wang X, Yu G, Zhao X (2020a) An evaluation of China's agricultural green production: 1978–2017. J Clean Prod 243:118483
Liu Y, Zou L, Wang Y (2020b) Spatial-temporal characteristics and influencing factors of agricultural eco-efficiency in China in recent 40 years. Land Use Policy 97:104794
Lu S, Sun Z, Huang M (2024) The impact of digital literacy on farmers' pro-environmental behavior: an analysis with the theory of planned behavior. Front Sustain Food Syst 8:1432184
Lu Y, Wang C, Yang R, Sun M, Zhang L, Zhang Y, Li XJ (2023) Research on the progress of agricultural non-point source pollution management in china: a review. Sustainability 15:13308
Luo J, Huang M, Bai Y (2024) Promoting green development of agriculture based on low-carbon policies and green preferences: an evolutionary game analysis. Environ Dev Sustain 26:6443–6470
Ma G, Zhou Z, Zhu C, Dan Y, wu Y (2020) Analysis on coupling coordination of livelihood capital and livelihood stability of farmers: a case of the Xiagu village in Huajiang demonstration area. Res Soil Water Conserv 27:230–237
Ma Q, Zheng S, Deng P (2022a) Impact of internet use on farmers' organic fertilizer application behavior under the climate change context: the role of social network. Land 11:1601
Ma Q, Zheng S, Lu Q (2022b) Social network, internet use and farmers' green production technology adoption behavior. J Arid Land Resour Environ, 36:16–21
Mao H, Zhou L, Ying R, Pan D (2021) Time preferences and green agricultural technology adoption: Field evidence from rice farmers in China. Land Use Policy 109:105627
Mapiye O, Makombe G, Molotsi A, Dzama K, Mapiye CJ (2023) Information and communication technologies (ICTs): The potential for enhancing the dissemination of agricultural information and services to smallholder farmers in sub-Saharan Africa. Information. Development 39:638–658
Molla A, Beuving J, Ruben RJ (2020) Risk aversion, cooperative membership, and path dependences of smallholder farmers in Ethiopia. Rev Dev Econ 24:167–187
Morris W, Henley A, Dowell D (2017) Farm diversification, entrepreneurship and technology adoption: analysis of upland farmers in Wales. J Rural Stud 53:132–143
Na H, Kang J (2023) Research on the impact of internet use on fertilizer and pesticide inputs: empirical evidence from China. Heliyon 9:e20816
Nie P, Ma W, Sousa-Poza A(2021) The relationship between smartphone use and subjective well-being in rural China. Electron Commerce Res 21:983–1009
Niu Z, Chen C, Gao Y, Wang Y, Chen Y, Zhao K (2022) Peer effects, attention allocation and farmers' adoption of cleaner production technology: taking green control techniques as an example. J Clean Prod 339:130700
Njau (2021) China Land Economic Survey, https://jiard.njau.edu.cn/info/1033/1675.htm, Access date [March 15, 2025]
Piancharoenwong A, Badir YF (2024) IoT smart farming adoption intention under climate change: The gain and loss perspective. Technol Forecast Soc Change 200:123192
Pray C, Nagarajan L, Li L, Huang J, Hu R, Selvaraj KN, Napasintuwong O, Babu RC (2011) Potential impact of biotechnology on adaption of agriculture to climate change: the case of drought tolerant rice breeding in Asia. Sustainability 3:1723–1741
Raj M, Gupta S, Chamola V, Elhence A, Garg T, Atiquzzaman M, Niyato DJ (2021) A survey on the role of Internet of Things for adopting and promoting Agriculture 4.0. J Netw Computer Appl 187:103107
Reddy PK, Ankaiah R (2005) A framework of information technology-based agriculture information dissemination system to improve crop productivity. Curr Sci 88:1905–1913
Ren Z, Fu Z, Zhong K (2022) The influence of social capital on farmers' green control technology adoption behavior. Front Psychol 13:1001442
Sarkar NC, Mondal K, Das A, Mukherjee A, Mandal S, Ghosh S, Bhattacharya B, Lawes R, Huda S (2023) Enhancing livelihoods in farming communities through super-resolution agromet advisories using advanced digital agriculture technologies. J Agrometeorol 25:68–78
Scharfy D, Boccali N, Stucki M (2017) Clean technologies in agriculture—how to prioritise measures? Sustainability 9:1303
Shen Z, Wang S, Boussemart J-P, Hao Y (2022) Digital transition and green growth in Chinese agriculture. Technol Forecast Soc Change 181:121742
Sher A, Mazhar S, Zulfiqar F, Wang D, Li XJ (2019) Green entrepreneurial farming: a dream or reality? J Clean Prod 220:1131–1142
Shuqin J, Fang Z (2018) Zero growth of chemical fertilizer and pesticide use: China's objectives, progress and challenges. J Resour Ecol 9:50–58
Sproten AN, Diener C, Fiebach CJ, Schwieren CJ (2018) Decision making and age: Factors influencing decision making under uncertainty. J Behav Exp Econ 76:43–54
Su F, Chang J, Zhang X, Fahad S, Aslam SBJ (2022) A pathway towards the development and evolution of consumer behavior: policy directions for sustainable development and improvement of nutrition. Front Nutr 9:1066444
Sui Y, Gao QJ (2023) Farmers' endowments, technology perception and green production technology adoption behavior. Sustainability 15:7385
Tobin J (1958) Estimation of relationships for limited dependent variables. Econometrica: J Econometric Soc 26:24–36
Vuong Q-H, Nguyen M-H, La V-P (2024) The overlooked contributors to climate and biodiversity crises: military operations and wars. Environ Manag 73:1089–1093

Weng F, Liu X, Huo X (2023) Impact of internet use on farmers' organic fertilizer investment: a new perspective of access to credit. Agriculture 13:219
Wu H, Wang B, Lu M, Irfan M, Miao X, Luo S, Hao Y (2023) The strategy to achieve zero-carbon in agricultural sector: does digitalization matter under the background of COP26 targets? Energy Econ 126:106916
Wu W, Liu R, He C, Yang L, Zhan D (2024) Research on the sustainable livelihoods of rural households based on livelihood capital: evidence from the natural rubber production area in Hainan and Yunnan provinces. Trop Geogr 44:746–760
Wu XD, Guo JL, Han MY, Chen GQ (2018) An overview of arable land use for the world economy: from source to sink via the global supply chain. Land Use Policy 76:201–214
Xie D, Gao W (2023) Low-carbon transformation of China's smallholder agriculture: exploring the role of farmland size expansion and green technology adoption. Environ Sci Pollut Res 30:105522–105537
Xie H, Huang YJ (2021) Influencing factors of farmers' adoption of pro-environmental agricultural technologies in China: Meta-analysis. Land Use Policy 109:105622
Xu D, Liu Y, Li Y, Liu S, Liu G (2024) Effect of farmland scale on agricultural green production technology adoption: evidence from rice farmers in Jiangsu Province, China. Land Use Policy 147:107381
Xu D, Qing C, Chen Y, He J, Zhang F (2023) Sustainable development of rural human settlements in the information age: can internet use drive farmers to participate in garbage classification? Agriculture 13:846
Xu D, Zhou W, Deng X, Ma Z, Yong Z, Qin CJ (2020) Information credibility, disaster risk perception and evacuation willingness of rural households in China. Nat Hazards 103:2865–2882
Yang C, Ji X, Cheng C, Liao S, Obuobi B, Zhang Y (2024) Digital economy empowers sustainable agriculture: Implications for farmers' adoption of ecological agricultural technologies. Ecol Indic 159:111723
Yu Y, Zhang J, Zhang K, Xu D, Qi Y, Deng X (2023) The impacts of farmer ageing on farmland ecological restoration technology adoption: empirical evidence from rural China. J Clean Prod 430:139648
Yuan F, Tang K, Shi Q (2021) Does internet use reduce chemical fertilizer use? Evidence from rural households in China. Environ Sci Pollut Res 28:6005–6017
Zhang J, Xie S, Li X, Xia X (2024) Adoption of green production technologies by farmers through traditional and digital agro-technology promotion–An example of physical versus biological control technologies. J Environ Manag 370:122813
Zhang J, Zhang R, Zhang K, Xu D, Qi Y, Deng X (2025) Does land management scale influence farmers' utilization of straw resources? Empirical evidence from rural China. Environ Impact Assess Rev 112:107820
Zhang Y, Wang L, Duan Y (2016) Agricultural information dissemination using ICTs: a review and analysis of information dissemination models in China. Inf Process Agric 3:17–29
Zhao Q, Pan Y, Xia X (2021) Internet can do help in the reduction of pesticide use by farmers: evidence from rural China. Environ Sci Pollut Res 28:2063–2073
Zhao W, Liang Z, Li B (2022) Realizing a rural sustainable development through a digital village construction: experiences from China. Sustainability 14:14199
Zheng H, Ma W, Wang F, Li G (2021) Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. Food Policy 102:102044
Zheng Y, Zhu T, Wei J (2022) Does Internet use promote the adoption of agricultural technology? Evidence from 1 449 farm households in 14 Chinese provinces. J Integr Agric 21:282–292
Zhong W, Chen Y, Xie L (2023) How does internet use promote joint adoption of sustainable agricultural practices? Evidence from rice farmers in China. Int J Agric Sustain 21:2270244
Zhou W, Qing C, Deng X, Song J, Xu D (2023) How does internet use affect farmers' low-carbon agricultural technologies in southern China? Environ Sci Pollut Res 30:16476–16487
Zhu J, Zheng S, Kaabar MKA, Yue X-G (2022) Online or offline? The impact of environmental knowledge acquisition on environmental behavior of Chinese farmers based on social capital perspective. Front Environ Sci 10:1052797
Zhu N, Guo Q, Wei T (2024) Impact of environmental regulation on the level of domestic waste classification among rural residents: a case study from rural China. Agriculture 15:41
Zhuang L, He J, Deng X, Xu DJ (2021) The influence of professionals on the general public in the choice of earthquake disaster preparedness: based on the perspective of peer effects. Int J Disaster Risk Reduct 66:102593
Zou L, Liu Y, Wang Y, Hu XJ (2020) Assessment and analysis of agricultural non-point source pollution loads in China: 1978–2017. J Environ Manag 263:110400
Zou Q, Zhang Z, Yi X, Yin C (2023) The direction of promoting smallholders' adoption of agricultural green production technologies in China. J Clean Prod 415:137734
Zou Y, Liu Z, Chen Y, Wang Y, Feng S (2024) Crop rotation and diversification in China: enhancing sustainable agriculture and resilience. Agriculture 14:1465

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Jialan Zhang: Writing – review & editing, Writing – original draft, Resources, Conceptualization. Ludan Zhang: Writing – original draft, Software, Methodology, Investigation, Data curation. Kuan Zhang: Writing – review & editing, Visualization. Xin Deng: Writing – review & editing, Resources, Funding acquisition, Project administration, Investigation, Conceptualization.

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve human participants.

Informed consent

Informed consent was not required as the study did not involve human participants.

Additional information

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