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Digital tools for soil stewardship: how Internet access drives farmland conservation in rural China?

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With the popularization of Internet technology in rural areas, its impact on sustainable agricultural development has become a hot research topic. Based on 1,728 farm household data from 14 provinces (districts), this paper employed the propensity score matching method and instrumental variable method to test and analyze the impact of Internet use on farm households' farmland quality protection behavior. The study found that the use of the Internet significantly promoted the farmer's cultivated land quality protection behavior. Compared to the non-Internet farmer, the use of the Internet enabled farmers to adopt an average of 0.318 more farmland quality protection technologies. Heterogeneity analysis shows that the use of the Internet is significantly positive among low-education farmers and villages with water security, and the role of the Internet is greater for trained farmers, small-scale farmers, high-income farmers, poor village farmers, and farmers in Western China. In addition, Internet use has a significant contribution to arable land quality protection measures such as straw return, deep ploughing and loosening, soil testing of fertilizers and planting of green manure crops. Therefore, the construction of rural Internet should be strengthened, and the heterogeneity of farmers and villages should be considered in policy formulation.

KEYWORDS

farmers, Internet use, cultivated land quality protection behavior, propensity score matching method, green technology (GT)

1 Introduction

Having fertile soil and sufficient grain reserves, enhancing the quality of arable land is not only a crucial measure to ensure national food security and improve the quality of agricultural products, but also a practical requirement for achieving sustainable agricultural development and enhancing the international competitiveness of agricultural products (Sileshi et al., 2019; Mideksa et al., 2023). However, China faces a significant degradation of arable land quality, currently. As a crucial indicator of soil quality, soil organic matter content in Chinese arable land is 10 g/kg, approximately 25–40% of Europe and the United States (Liu et al., 2020; Fan et al., 2012). The degradation of arable land quality not only results in reduced grain production and diminished agricultural product quality, but also leads to an increase in agricultural production costs. Ultimately, this deterioration adversely impacts the sustainability of agricultural development (Masebo et al., 2014). Despite the government implementing various policy measures to encourage and promote the widespread adoption of technologies for arable

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land quality protection,[1] as the primary operators and beneficiaries of agricultural production, farmers' actions play a pivotal role in determining the level of arable land quality.

The existing research has explored farmers' behavior in protecting farmland quality from various perspectives. The higher the awareness among farmers regarding land degradation, the more willing they are to adopt soil conservation measures (Abdeta et al., 2018). Farmers with stronger local identity and local attachment are more likely to engage in land quality protection behaviors, and self-efficacy reinforces the role of local identity and local attachment (Li H, et al., 2023), and the impact of local attachment varies depending on farmers' levels of environmental awareness and age (Wang et al., 2021). Farmers with a higher awareness of farmland quality protection are more inclined to adopt farmland conservation measures (Liu, 2018). The higher the degree of diversification in farmers, the lower their investment in farmland quality protection (Yang et al., 2015). Land tenure security is a fundamental factor that motivates farmers to adopt sustainable land management measures. Compared to tenants, owners adopt soil improvement practices at a frequency 1.9 times higher. A carefully designed, environment-driven subsidy system can help bridge the significant gap in soil conservation attitudes between owners and tenants (Sklenicka et al., 2015). From the perspective of the development level of land transfer markets, when the land transfer market is underdeveloped, farmers are less likely to engage in farmland quality protection practices upon acquiring land. However, as the land transfer market matures, there is an increase in farmers' adoption of farmland quality protection behaviors (Long and Ren, 2017; Li and Shen, 2021). From the perspective of land tenure stability, land certification increases land tenure security, motivating farmers to invest in organic fertilizers. For contracted land, land certification promotes farmland quality protection behaviors. However, for acquired land, land certification only encourages farmers to reduce chemical fertilizer use, with no impact on the adoption of organic fertilizers or straw return techniques (Zhou and Wang, 2019; Holden et al., 2009; Zhou et al., 2022). Farmers' limited adoption or non-adoption of soil conservation techniques is often not due to a lack of the technologies themselves but rather stems from the absence of favorable policy and institutional environments. While subsidies and other forms of incentives are employed to encourage the adoption of specific technologies, they may not fully address farmers' concerns, leading to unsustainable adoption practices (Bagheri and Teymouri, 2022). Effective profitability is the primary motivating factor for farmers to adopt soil conservation practices (SCPs), surpassing ecological attitudes or government subsidies. Additionally, farm size has the greatest impact on the choice of soil conservation measures (Fantappiè et al., 2020).

As research progresses, scholars have begun to focus on the impact of information on farmers' behaviors related to farmland quality protection. Farmers' information acquisition (cooperatives, technical training) has a significant positive impact on their soil testing, formula fertilizer and organic fertilizer investment (Chu and Zhang, 2012). Social learning can create more opportunities for farmers to understand soil conservation and facilitate the adoption of soil protection measures. In this context, farmer organizations and their institutions are considered key leaders and facilitators of social learning (Dessie et al., 2013). Cooperatives can bring more information to farmers, thereby promoting the adoption of organic fertilizer input (Ma et al., 2018). However, there has been limited research focusing on the impact of Internet usage on farmers' farmland quality protection.

The Internet, as a crucial avenue and tool for farmers to acquire information, profoundly influences farmers' perspectives and behavioral habits, gradually emerging as a new force in the development of agriculture in China. On one hand, the Internet reduces transaction costs for farmers in obtaining information, making it more convenient for them to access timely and accurate agricultural production information. This includes guidance on scientifically and reasonably applying fertilizers in agriculture, information on agricultural product market prices, and updates on agricultural policies (Zhu et al., 2021; Li J, et al., 2023). Aker (2010) found that mobile phones could reduce price dispersion by 10–16%, with a greater impact on markets where transportation costs are higher. Similarly, Cole and Fernando (2012) indicates that as the demand for phone-based agricultural advisory services increases among farmers, they are more inclined to adopt agricultural technologies, including high-value and high-risk export crops. On the other hand, the Internet disseminates various ecological information to farmers through text, voice, images, and videos. Additionally, farmers can express their personal views and opinions on the current agricultural environment through the Internet. Gradually, this process influences and transforms farmers' environmental awareness, enhancing their environmental literacy (Ma et al., 2022). Peng and Li (2019) based on data from the China General Social Survey, found that the Internet has the potential to facilitate the improvement of individuals' environmental attitudes and enhance their environmental literacy. Consequently, this can further stimulate environmentally friendly behaviors among people. Similarly, Yan and Liu (2020), as per their findings, discovered that mobile phones have the capacity to influence farmers' perceptions of sustainable development and awareness of pesticide application standards, thereby promoting the adoption of Integrated Pest Management (IPM) techniques. Furthermore, the Internet enables farmers to access modern management concepts, facilitating their transition from traditional farming practices to becoming professional farmers. Certainly, scholars have paid attention to the impact of Internet use on farmers' land conservation measures. For instance, Weng et al. (2023) argue that the presence of information asymmetry in the organic fertilizer market and credit constraints in financial markets hinder farmers' enthusiasm for using organic fertilizers. The use of the Internet effectively mitigates the degree of rural information asymmetry, promoting farmers' investment in organic fertilizers. Khan (2021), based on a survey conducted in rural Afghan households, discovered that mobile phone usage significantly reduces the use of inorganic fertilizers among farmers. However, existing research has primarily focused on exploring the impact of Internet use on specific soil conservation measures within the agricultural production process. Since farmers engage in various soil conservation measures throughout the agricultural production process, it is crucial to consider the influence of Internet use on multiple soil conservation measures throughout the entire agricultural production process.

1 "National Agricultural Sustainable Development Plan (2015–2030)" (2015, Ministry of Agriculture and Rural Affairs, etc.), "Action Plan for Protection and Improvement of Farmland Quality" (2017, Ministry of Agriculture and Rural Affairs), etc.

The Chinese government places a high emphasis on "Internet Plus" agriculture. In 2015, as part of its governmental work agenda, China introduced the "Internet Plus" strategy with the aim of leveraging technologies such as the Internet and big data to revitalize traditional industries that were showing signs of fatigue. In 2016, the Ministry of Agriculture and Rural Affairs, along with eight other departments, issued the "Three-Year Action Implementation Plan for 'Internet Plus' Modern Agriculture," aiming to transform traditional agriculture using the Internet. In 2019, the General Office of the Central Committee of the Communist Party of China and the General Office of the State Council issued the "Outline of the Digital Village Development Strategy," explicitly stating the need to promote the digital transformation of agriculture and advance the deep integration of the Internet with agriculture. In 2022, China's Central Document No.1 explicitly introduced the concept of the "Digital Business Boosts Agriculture" project for the first time. In 2023, the National Development and Reform Commission and the National Bureau of Statistics issued the "Implementation Plan for Promoting Common Prosperity through the Digital Economy," emphasizing the in-depth development of the "Digital Business Boosts Agriculture" initiative and the implementation of the "Internet Plus" project for bringing agricultural products from villages into cities. Against this backdrop, it is of significant practical importance to examine the impact of Internet use on the land quality protection behaviors of Chinese farmers, focusing on micro-level data. Building upon this, the present study utilizes survey data from the National Academy of Agriculture and Rural Development at China Agricultural University, collected during the period of January to March 2019. The study aims to delve into the detailed impact of Internet use on farmers' behaviors related to the protection of land quality. The marginal contributions of this paper are as follows: Firstly, based on micro-level data from Chinese farmers, it explores the impact of Internet use on the quality of farming from the perspective of Internet usage. It examines the heterogeneity of the influence of Internet use on farmers' adoption of land quality protection technologies at the levels of individual farmers, households, villages, and regions. Secondly, in contrast to previous research that focused solely on individual soil conservation measures, this study comprehensively considers multiple soil conservation measures throughout the agricultural production process. It provides a more comprehensive exploration of the impact of Internet use on farmers' land quality protection behaviors.

The remaining structure of this paper is as follows: The second section presents theoretical analysis, primarily exploring the mechanisms through which Internet use influences farmers' land quality protection behaviors. The third section covers data sources, variable selection, and model choices. The fourth section delves into empirical results and analysis. The fifth and final section comprises conclusions and policy recommendations.

2 Theoretical analysis

2.1 Construction of the evolutionary game model

2.1.1 Evolutionary game theory

Evolutionary game theory is a general analytical framework for studying agent interactions and strategy selection. It establishes evolutionary game models centered on the replicator dynamic equations and evolutionary stable states, which, respectively, represent the stable states of an evolutionary game and the dynamic convergence process toward such states (Rui, 2024). Compared with static equilibrium analysis, evolutionary game theory better captures the dynamic evolution of group behavior and is particularly suitable for situations involving continuous interaction and strategy adjustment (Coninx et al., 2018; Xie et al., 2018).

In farmers' production decisions, whether to adopt Internet technologies depends not only on their own returns but also on the behaviors of other farmers and the technological environment, exhibiting typical characteristics of group interaction. Therefore, introducing evolutionary game theory enables a deeper exploration of the decision-making evolution mechanism of farmers' Internet use and cultivated land protection behavior, providing a solid logical foundation for the formulation of theoretical hypotheses and subsequent empirical testing.

2.1.2 Model assumptions and construction

> Assumption 1: Farmers are conceptualized as two groups, A and B, who maintain bounded rationality and seek optimal strategies through repeated games.
>
> Assumption 2: Both groups A and B have two strategic choices: "Protect cultivated land" and "Not protect" (hereafter abbreviated as "Protect" and "Not Protect"). The probability of choosing "Protect" is denoted as x $(0 \le x \le 1)$ and y $(0 \le y \le 1)$, while that of choosing "Not Protect" is $(1 - x)$ and $(1 - y)$, respectively.
>
> Assumption 2: When choosing "Protect," farmers' return is R_1, with an operating cost of C_1, and they also incur an Internet learning cost C_2. When choosing "Not Protect," the return and cost are R_2 and C_3, respectively, and there is a probability β of land degradation leading to a loss L.
>
> Assumption 4: "Not Protect" generates negative externalities. Let K_i $(i = 1,2)$ represent the risk coefficient borne by the protecting party when the other party does not protect. Since groups A and B are homogeneous, $K_1 = K_2 = K$.

Based on these assumptions, the payoff matrix is shown in Table 1.

The evolutionary process of strategies for groups A and B can be expressed by the replicator dynamic equations:

$$F(x) = x\left(E_{11} - \overline{E_1}\right) = x(1-x)\left(R_1 - R_2 + C_3 - C_1 - C_2 - (1-y)K\beta L + \beta L\right) \quad (1)$$

$$F(y) = y\left(E_{21} - \overline{E_2}\right) = y(1-y)\left(R_1 - R_2 + C_3 - C_1 - C_2 - (1-x)K\beta L + \beta L\right) \quad (2)$$

2.1.3 Stable strategies and equilibrium analysis

When groups A and B engage in repeated games and no longer change their strategies, the strategy combination reaches an evolutionary stable state (ESS). To obtain the local stationary points and system stability points of the dynamic system, we set Equations 1, 2 equal to zero, indicating no further change in

TABLE 1 Payoff matrix of groups A and B.

Game agent and selected strategy		Group B	
		Protect (y)	Not protect (1-y)
Group A	Protect (x)	$R_1 - C_1 - C_2$	$R_1 - C_1 - C_2 - K\beta L$
		$R_1 - C_1 - C_2$	$R_2 - C_3 - \beta L$
	Not protect (1-x)	$R_2 - C_3 - \beta L$	$R_2 - C_3 - \beta L$
		$R_1 - C_1 - C_2 - K\beta L$	$R_2 - C_3 - \beta L$

strategies. Five local equilibrium points are derived: $E_1(0,0), E_2(1,0), E_3(0,1), E_4(1,1), E_5(x^*,y^*), x^* \in [0,1], y^* \in [0,1]$. The stability of these points is analyzed using the Jacobian matrix: if the determinant of the Jacobian is greater than 0 and the trace is less than 0, the point is an ESS; if the trace equals 0, it is a saddle point; otherwise, it is unstable (Friedman, 1998). Among the five equilibrium points, E_1 and E_4 are ESS, E_2 and E_3 are unstable, and E_5 is a saddle point. The evolutionary game paths of groups A and B are shown in Figure 1. The ratio of the area $E_1E_2E_5E_3$ to the total area represents the probability of the system evolving to E_1 *(0,0)*, i.e., $P_0 = \frac{x^* + y^*}{2}$; the ratio of the area $E_2E_3E_5E_4$ to the total area represents the probability of evolving to E_4 *(1,1)*, i.e., $P_1 = 1 - \frac{x^* + y^*}{2}$.

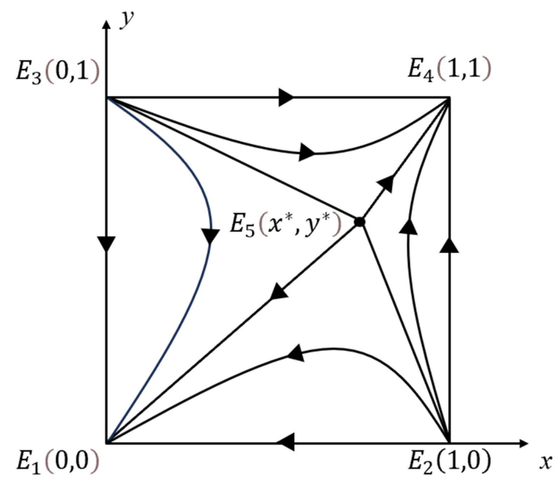

FIGURE 1
Evolutionary game paths.

2.2 Mechanism analysis

At present, leveraging the Internet to influence farmers' production behaviors, transform agricultural development patterns, and upgrade the agricultural industry has become a major priority for governments. On the one hand, the Internet broadens farmers' access to information, reduces decision-making costs arising from information asymmetry, and enables easier access to agricultural technologies, market trends, and policy updates, thereby boosting agricultural productivity and income (Xiaoyan et al., 2024). On the other hand, the Internet enhances farmers' environmental literacy. Through online platforms and new media, farmers can better understand the importance of cultivated land protection and green production, strengthen environmental awareness and gradually shape a sustainable development orientation. These two pathways interact and jointly promote the green and sustainable transformation of agriculture.

Information Acquisition. As a vital channel and tool for information, the Internet enables farmers to access market, technological, and policy information (Li J, et al., 2023; Weng et al., 2023). While neoclassical economics assumes perfect and fully competitive markets, in reality, farmers often face information asymmetry and market price fluctuations, raising concerns about where, how, and to whom to sell. According to the new household economics theory, the price farmers receive depends on the degree of market imperfection, measured by transaction costs, with information search cost being a key component. The Internet, as a new technology, effectively reduces information costs (Aker and Mbiti, 2010). Farmers can obtain real-time price information and forecast trends, thereby adjusting current production decisions.[2] Similarly, they can quickly and accurately learn about new technologies, assess their risks and benefits, and master application procedures, reducing uncertainty and adoption risk (Yan and Liu, 2020). Furthermore, the Internet provides timely access to agricultural policies. Under the current rural revitalization strategy, Internet use enhances policy awareness and helps farmers identify market opportunities, thus promoting technology adoption. Survey data show that the policy awareness index among Internet-using farmers is 0.842, compared with 0.716 among non-users.

Improvement of Environmental Literacy. Internet use also affects farmers' environmental awareness, knowledge, and behavior. Generally, negative information has a greater psychological impact than positive information (Ito et al., 1998). Internet users, accustomed to rapid information intake, develop stronger perceptions of environmental problems, realizing they concern not only the state but also personal well-being. Out of self-interest, farmers adjust their environmental stance and adopt positive environmental values. From an evolutionary psychology perspective, humans exhibit a "negative bias," often sharing negative information such as environmental pollution news (Rozin and Royzman, 2001), which further amplifies pollution perception. Meanwhile, the Internet provides an effective platform for disseminating environmental knowledge, policies, and practices, enriching farmers' knowledge base and enabling equal access across different educational levels. Farmers can also actively participate in environmental governance: they can learn about penalties for violations, comply with environmental regulations, and report misconduct, while also gaining methods and tools for environmental protection. Improved awareness, knowledge, and behavior foster higher environmental literacy, which in turn increases

2 In the survey, the anticipation of future agricultural product prices is categorized into three groups: decreasing = 1; uncertain = 2; increasing = 3. The average for farmers using the Internet is 1.056, higher than the average for farmers not using the Internet, which is 0.932.

farmers' likelihood of adopting eco-friendly technologies (Wyckhuys et al., 2019).

Whether farmers adopt land protection measures is ultimately a cost–benefit decision (Atampugre, 2014). Combined with the evolutionary game model, since $\frac{\partial x^*}{\partial(R_1 - R_2)} < 0$ and $\frac{\partial x^*}{\partial(C_3 - C_1 - C_2)} < 0$, Internet use can, on the one hand, lower information search costs and improve access to market, technical, and policy information, thereby increasing returns. On the other hand, it enhances environmental literacy by shaping awareness, knowledge, and behaviors. Under these conditions, the payoff gap between the two strategies expands, x^*, y^* evolve toward E_1 (0,0), and P_1 increases, meaning the probability of system evolution toward E_4 (1,1) rises. Based on this, a theoretical framework illustrating the impact of Internet use on farmer's cultivated land quality protection behavior is constructed, as shown in Figure 2.

3 Data, variables and models

3.1 Data sources

A multi-stage random sampling method was employed. First, based on the regional distribution of agricultural production and the status of major grain-producing provinces in China, 14 provinces (autonomous regions) were selected as target areas. Second, within each target province (autonomous region), representative counties (districts) were chosen by comprehensively considering factors such as economic development level, terrain, and agricultural structure. Subsequently, in each selected county (district), 3–5 typical villages were chosen (usually the hometowns of surveyors or villages familiar to them, while ensuring alignment with the county's agricultural-economic characteristics). In each village, 15–20 households were randomly sampled. Household selection within villages typically followed one or a combination of the following methods to ensure randomness: (1) if a complete household roster was available, households were selected using a random number table or systematic sampling; (2) if no roster was available, equal-interval sampling (e.g., based on house numbers or geographic spacing) or the random walk method (starting from the village center and selecting households at fixed intervals along a predetermined path) was employed.

For data quality control, the research team established a review and incentive mechanism: surveyors who submitted high-quality questionnaires received appropriate rewards, while low-quality questionnaires were discarded, and compensation was adjusted accordingly. To further ensure data validity, the team conducted random follow-ups, cross-validation, and multi-level review processes. A total of 1,952 questionnaires from grain-cultivating households were collected. During data processing, village-level and household-level questionnaires were matched, and unmatched, missing, or anomalous entries were removed, resulting in a final sample of 1,725 household questionnaires from 14 provinces (autonomous regions), 130 counties (districts), and 151 villages. The 14 provinces (autonomous regions) include Inner Mongolia, Jilin, Sichuan, Anhui, Shandong, Jiangsu, Jiangxi, Hebei, Henan, Hubei, Hunan, Gansu, Liaoning, and Heilongjiang, covering eastern, central, western, and northeastern China, thereby providing good representativeness.

3.2 Variable selection

3.2.1 Dependent variable—land quality protection behavior

Due to the fact that farmers' land quality protection behavior is reflected in the adoption of land quality protection technologies, following the approach of Willy and Holm-Müller (2013), the quantity of land quality protection technologies adopted by farmers is used to represent farmers' land quality protection behavior. Farmers' land protection behavior in agricultural production manifests in various aspects. Referring to the provisions of the National Plan for Agricultural Sustainable Development (2015–2030), practices to improve land quality include adopting deep plowing and loosening, conservation tillage, straw returning, increased application of organic fertilizers, and planting cover crops as soil improvement methods. The main aspects used to measure farmers' land protection behavior in the

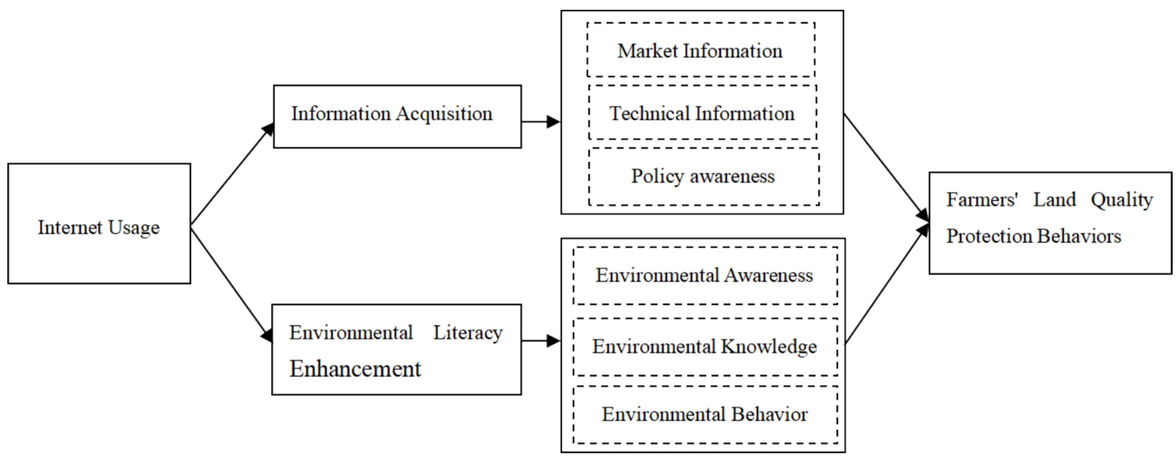

FIGURE 2
Theoretical framework of Internet use and land protection behavior.

text include six factors: straw returning, deep plowing and loosening, soil testing and formula fertilization, no-tillage seeding, planting cover crops, and increased application of organic fertilizers. For each of these technologies, a value of 1 is assigned if adopted and 0 if not adopted. Therefore, the number of land protection measures adopted by farmers ranges from 0 to 6. The adoption rates for straw returning, deep plowing and loosening, soil testing and formula fertilization, no-tillage seeding, planting cover crops, and increased application of organic fertilizers are 60.94, 48.44, 20.20, 13.08, 12.38, and 19.73%, respectively.

3.2.2 Core independent variable—Internet use

Studies show that merely having access to the Internet is not sufficient to improve production efficiency; the key lies in whether it is used to obtain agriculture-related information (Li et al., 2024). Considering that farmers may own smartphones or possess Internet skills but do not necessarily use them to acquire agricultural information, this study directly asks farmers whether they use the Internet to obtain agricultural production information.

3.2.3 Control variables

Based on the rational smallholder theory of farmer behavior, and drawing on relevant domestic and international research, this study also examines the factors influencing farmers' adoption of green production technologies from two dimensions: internal endowments and external environment. Specifically, three categories of control variables are introduced:

Individual characteristics of farmers. These mainly include age, education level, health status, training experience, risk preference, and policy awareness, reflecting farmers' individual capabilities, cognition, and decision-making tendencies. Younger, better-educated, and healthier farmers are more willing to adopt green production technologies (Fan et al., 2024); training experience significantly enhances their awareness and operational ability regarding green technologies, thereby increasing adoption rates (Sun et al., 2020); risk preference directly affects farmers' adoption decisions under uncertainty, with more risk-averse farmers tending to stick to traditional production technologies (Chen et al., 2025); policy awareness determines their understanding of government subsidies and promotion policies, thereby influencing their willingness to adopt (Rizzo et al., 2024).

Household operational characteristics. These include labor force size, farm size, number of plots, land quality, household income, subsidy level, and the share of non-farm income, reflecting the endowment of household production factors and economic status. A sufficient household labor force helps meet the extra labor demand of green technologies (Bukchin and Kerret, 2018); farm size and number of plots determine whether farmers have the potential for large-scale trials and adoption of green technologies, while land quality affects the marginal benefits of adoption (Fan et al., 2024); higher household income and subsidy levels help ease financial constraints and reduce the cost pressure of adoption (Wu, 2022); the share of non-farm income may generate a "crowding-out effect" on agricultural investment, thereby weakening adoption willingness, but it may also increase willingness to adopt due to more abundant financial resources (Xie and Huang, 2021).

Village characteristics. These include whether the village is classified as poor, its economic development level, water resource security, and distance to major roads. Farmers in poor villages may adopt technologies less due to constraints in resources and information; higher village-level economic development enhances social demonstration effects and information diffusion, thereby increasing adoption willingness (Mu et al., 2024); water security is directly linked to the applicability and sustainability of green agricultural technologies, while transportation accessibility affects farmers' ability to obtain inputs, receive external services, and access markets, indirectly influencing adoption (Aggarwal et al., 2024).

Descriptive statistics of the relevant variables are presented in Table 2.

3.3 Model selection

3.3.1 Propensity score matching

Due to the non-random sampling of farmers' Internet usage, which is a result of "self-selection," there exists systematic differences in the initial conditions (primarily referring to farmers' age, education level, and risk preference) before they use the Internet. Direct regression analysis may lead to selection bias. Therefore, this study employs Propensity Score Matching (PSM) to address this issue by constructing counterfactuals. The specific steps are as follows:

First, employ a Logit model to estimate the probability of farmers' Internet usage and calculate the propensity score, as shown in Equation 3:

$$\mathrm{P}(\mathrm{x}) = \mathrm{F}\left(\mathrm{Internet}_i = 1 \middle| X\right) = \frac{1}{1+e^{-y}} \tag{3}$$

Second, utilize nearest neighbor matching, kernel matching, radius matching, and Mahalanobis matching methods to obtain the treatment group and control group, thus mitigating the issue of self-selection.

Third, based on the matched samples obtained above, compare the average difference in the number of adopted land conservation techniques between the treatment group and the control group, i.e., the Average Treatment Effect on the Treated (ATT).

$$ATT = \mathrm{E}\left[\left(Y_1 - Y_0\right)\middle| D = 1\right] = E\left\{\mathrm{E}\left[\left(Y_1 - Y_0\right)\middle| D = 1\right], P\left(X\right)\right\} \tag{4}$$

As shown in Equation 4, D is a binary variable with values of 0 and 1, where D = 1 represents the treatment group and D = 0 represents the control group. P(x) represents the propensity score, while Y1 and Y0 denote the estimated outcomes for farmers using the Internet and those not using the Internet, respectively.

3.3.2 Instrumental variable method

The basic regression model is shown in Equation 5:

$$\mathrm{Till}_i = \beta_0 + \beta_1 internet_i + \gamma z_i + \delta region_i + \varepsilon_i \tag{5}$$

Where z_i represents control variables, γ denotes the coefficient vector of control variables, $region_i$ stands for regional variables, δ is the coefficient of regional variables, and ε_i is the error term. Due to the potential endogeneity issue in farmers' Internet usage, this study further employs Two-Stage Least Squares (2SLS) to address the endogeneity problem.

In the first stage, regress the endogenous variable on the instrumental variable to obtain the fitted values $\hat{p}_t$.

TABLE 2 Descriptive statistical analysis of variables.

Variable type	Variable	Variable definitions	Sample size	Mean	standard deviation
Dependent variable	Land quality protection behavior	Number of land quality protection technologies adopted (number)	1728	1.748	1.242
Core independent variables	Internet usage	Whether to use the Internet to obtain agricultural production information, yes = 1; no = 0	1728	0.177 _	0.381 _
Control variables	Age	Unit: Years	1728	53.389	11.234
	Education level	Illiteracy = 1; primary school = 2; junior high school (secondary vocational school) = 3; high school (technical secondary school) = 4; college (higher vocational school) = 5; college or above = 6	1728	2.72	0.93 _
	Health status	Good = 1; Fair = 2; Poor = 3; Incapable of working = 4	1728	1.406	0.614 _
	Training	Yes = 1; No = 0	1728	0.225 _	0.418 _
	Number of labor force	Number of family agricultural labor force	1728	2.195	1.04
	Risk appetite	Risk conservative = 1; Risk neutral = 2; Risk preference = 3	1728	1.43	0.644 _
	Policy awareness	"Do you know the policy of extending the second round of contracting for another 30 years upon expiration "? Know = 1; Do not know = 0	1728	0.738 _	0.44 _
	Business scale	Current household business scale (mu)	1728	2.243	1.127
	Number of plots	Number of operating plots (blocks)	1728	5.744	16.561
	Farmland quality	The land is poor = 1; the land quality is below average = 2; the land quality is medium = 3; the land quality is above average = 4; the land is very fertile = 5	1728	3.078	0.851 _
	Household income	Various sources of household income, including agricultural business income, non-agricultural income, property income, disaster relief income and other income (yuan), taking the logarithm	1728	10.631	1.078
	Subsidy	Three subsidies, agricultural machinery subsidies, subsidies for large grain growers, production technology subsidies, agricultural insurance premium subsidies, loan interest discounts, etc. (yuan), take the logarithm	1728	5.802	2.388
	Proportion of non-agricultural income	The proportion of household non-agricultural income in total household income	1728	0.632 _	0.345 _
	Poor village	Yes = 1; No = 0	1728	0.238 _	0.426 _
	Economic level	Superior = 1; upper-medium = 2; medium = 3; lower-middle = 4; inferior = 5	1728	3.236	0.907 _
	Water source security	Yes = 1; No = 0	1728	0.763 _	0.425 _
	Highway distance	The distance (km) between the village and the nearest highway trunk line (provincial highway or highway entrance), take the logarithm	1728	1.635	1.245

In the second stage, regress the dependent variable on the fitted values obtained from the first stage regression to obtain the regression coefficients.

Following the approach of Ling et al. (2018) and Liu et al. (2014), this study selects "neighborhood Internet penetration" as its instrumental variable, as shown in Equation 6:

$$peer\_internet_{-i}^{c} = \frac{\sum_{N^c} internet^{c} - internet_{i}^{c}}{N^{c} - 1} \tag{6}$$

Where $internet_i^c$ represents the Internet level of household i in village c, $\sum_{N^c} internet^c$ is the total sum of Internet levels for all households in village c, and $peer\_internet_{-i}^{c}$ denotes the average Internet level of other households in the same village except household i, which represents the neighborhood Internet penetration. N^c represents the total number of households in village c.

4 Empirical results and analysis

4.1 Propensity score matching results

In this section, propensity score matching is used to address the issue of self-selection in Internet usage. To ensure the robustness of the conclusions, various matching methods are employed to obtain the average treatment effect on the treated (ATT) of the adoption of soil conservation techniques for farmers using and not using the

TABLE 3 PSM regression results.

Matching method	Treatment group	Control group	ATT	Standard error	*t* value
Four nearest neighbor matching	2.047	1.717	0.330 ***	0.091	3.64
Kernel matching	2.047	1.730	0.316 ***	0.084	3.76
Radius matching	2.047	1.727	0.320 ***	0.084	3.80
Mahalanobis matching	2.046	1.739	0.307 ***	0.065	4.70

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

TABLE 4 Heterogeneity analysis based on farmer characteristics.

Statistics	Education level		Training	
	Low educated farmers	Highly educated farmers	Receive training	Not trained
ATT	0.312*** (0.1079)	−0.123 (0.2061)	0.624*** (0.2287)	0.097** (0.1017)
N	1,436	292	389	1,339

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Internet (treatment group and control group), as shown in Table 3. It can be observed that under different matching methods, the ATT values are all positive and statistically significant at the 1% level, indicating that Internet usage significantly promotes farmers' adoption of soil conservation behaviors. To further explore the magnitude of the impact of Internet usage on farmers' soil conservation behaviors, we take the widely used nearest neighbor matching method as an example. Due to the large variance associated with one-to-one matching in nearest neighbor matching, Abadie (2004) suggest choosing one-to-four matching to minimize mean squared error. Therefore, we primarily focus on the detailed analysis of four nearest neighbor matching. The ATT value for one-to-four nearest neighbor matching is 0.330, indicating that compared to farmers who do not use the internet, Internet usage leads to an increase of 0.330 units in the adoption of soil Conservation technologies by farmers. The ATT values obtained from other matching methods are all at 0.300 or above. The average ATT across different matching methods is 0.318.

The paper further conducts balance tests on the matching results. After matching, the standardized bias (%) for most variables decreases, and most t-tests are not significant, indicating that the null hypothesis of no systematic significant differences between the treatment group and the control group cannot be rejected.[3]

4.2 Heterogeneity analysis

The above analysis only examined the average effect of Internet usage on farmers' land quality protection behavior, without considering the heterogeneity across farmers, households, villages, and regions. In this paper, we conduct heterogeneity analysis based on these four aspects (using four nearest neighbor matching).

From the perspective of farmer characteristics, considering that education levels are generally low in rural areas, this study categorizes farmers with junior high school education or below as low-education farmers, and those with high school education or above as high-education farmers. As shown in Table 4, for low-education farmers, the ATT value is significantly positive, indicating that the effect of the Internet on low-education farmers is greater. This could be because low-education farmers face greater difficulty in accessing information, and using the Internet can significantly enrich their information resources, leading to the adoption of more land quality protection measures. Farmers who have received training exhibit a significantly higher ATT value compared to those who have not received training. This may be because farmers who undergo training are able to acquire more agricultural information and Internet skills, which in turn promote the adoption of more land quality protection measures through Internet usage (Zeng et al., 2022; Lobry de Bruyn et al., 2017).

From the perspective of family characteristics, referring to the World Bank's classification criteria for smallholder farmers, those with less than 30 mu of land are categorized as small-scale farmers, while those with 30 mu or more are categorized as large-scale farmers. As shown in Table 5, small-scale farmers exhibit significantly higher ATT values compared to large-scale farmers. This could be because small-scale farmers are more flexible in their operations, while large-scale farmers may require higher production costs (Weng et al., 2023; Abdul-Hanan et al., 2014). For income levels, using the sample's average income of 71,402 as the threshold, households with incomes below the average are categorized as low-income households, while those with incomes above the average are categorized as high-income households. High-income households exhibit significantly higher ATT values. This could be because high-income households have more financial resources to invest in land conservation measures (Bayard et al., 2006; Tiwari et al., 2008).

From village characteristics, as shown in Table 6, households in villages with guaranteed water sources exhibit significantly higher ATT values. This could be because villages with secure water sources have better agricultural production conditions, and farmers are more willing to invest in agriculture to earn more income. Additionally, households in impoverished villages have higher ATT values, possibly because farmers in impoverished villages rely more on agricultural income. The use of the Internet can increase farmers' awareness of land conservation measures, prompting them to adopt more of these measures to increase agricultural income (Chen et al., 2022).

3 Due to space limitations, the balance test results are not shown. If necessary, they can be obtained from the author.

TABLE 5 Heterogeneity analysis based on family characteristics.

Statistics	Business scale		Income level	
	Small scale farmers	Large scale farmers	Low income level	High income level
ATT	0.449*** (0.1200)	0.356* (0.2045)	0.270** (0.1203)	0.404*** (0.1418)
N	1,441	287	1,194	534

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

TABLE 6 Heterogeneity analysis based on village characteristics.

Statistics	Water source security		Economic level	
	Water source is guaranteed	Water source is not guaranteed	Poor village	Non-poor village
ATT	0.374*** (0.1059)	−0.299 (0.2174)	0.556** (0.2275)	0.244** (0.1059)
N	1,319	409	412	1,316

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

TABLE 7 Heterogeneity analysis based on regional characteristics.

Statistics	East	Central	West
ATT	0.420** (0.1748)	0.337** (0.1345)	0.705*** (0.2110)
N	589	766	373

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

From regional characteristics, as shown in Table 7, the ATT values are significantly positive in the eastern, central, and western regions. Upon further comparison, the northwest region has a higher ATT value. This could be because farmers in the western region rely more on agricultural income and adopt more land conservation measures to increase their agricultural income. Regarding the eastern and central regions, the ATT value is significantly higher in the eastern region. This may be because the eastern region is more economically developed, and farmers have a higher awareness of environmental protection, thereby adopting relatively more land quality protection measures (Khan, 2021).

4.3 Scalability analysis

The above analysis explored the impact of Internet usage on the adoption of land quality protection measures by farmers, but this may obscure the effects of Internet usage on individual land quality protection measures. Therefore, this section specifically analyzes the impact of Internet usage on each land quality protection measure, as shown in Table 8.

For nearest neighbor matching, kernel matching, radius matching, and Mahalanobis matching, the ATT values for straw returning, deep plowing, soil testing and formula fertilization, and planting green manure crops are all significantly positive (the t-value for planting green manure crops in the 4-nearest neighbor matching is 1.63, and the ATT values for other matching methods are significant at the 10% level). This indicates that the probability of farmers adopting these four land quality protection measures is significantly higher for Internet-using farmers compared to those who do not use the Internet. However, the adoption of no-till seeding and organic fertilizer use is not significant. This might be because no-till seeding and organic fertilizer application are substitutes for deep plowing and soil testing and formula fertilization techniques. In rural areas where deep plowing and soil testing and formula fertilization techniques are more widely promoted and farmers have higher awareness, they are more likely to adopt deep plowing and organic fertilizer techniques.

4.4 Robustness test

To make the conclusions more robust, this study employs four methods of robustness checks: instrumental variable approach, sample adjustment, core variable adjustment, and model adjustment.

Instrumental Variable Approach: Due to the possibility that the more agricultural conservation measures adopted by farmers, the more likely they are to use the Internet to access agricultural information, endogeneity issues may arise in Internet usage. The Hausman endogeneity test is significant at the 10% level, indicating rejection of the hypothesis of no endogeneity. Drawing from the research approach of Li and Ma (2019), this study employs neighborhood Internet level as an instrumental variable. From the perspective of correlation, in rural communities characterized by social networks, there exists a behavioral imitation effect among farmers (Bagheri and Teymouri, 2022). In terms of endogeneity, the neighborhood Internet level does not directly influence the current agricultural conservation behavior of farmers. The C-D Wald statistic is relatively large, indicating rejection of the weak instrument assumption for neighborhood Internet level. As seen in Table 10, the coefficient of the instrumental variable is significantly positive in the first-stage regression, and similarly, the coefficient of Internet usage is also significantly positive at the 1% level in the second-stage regression. This suggests that after addressing endogeneity, relative to farmers who do not use the Internet, Internet-using farmers adopt an average of 0.451 more agricultural conservation measures.

Sample adjustment. Considering that individuals over 60 years old generally have lower agricultural productivity, only samples of farmers under 60 are retained. As shown in Table 9, the ATT value is significantly positive. Moreover, due to significant differences in agricultural production conditions and national agricultural strategic positioning in the Northeast region compared to other regions, samples from the Northeast region are excluded. The results still show a significantly positive ATT value.

Adjusting core independent variables. Due to the correlation between whether farmers "publish online sales information," "online

TABLE 8 Impact of Internet use on the adoption of each farmland quality protection technology.

Matching method	Straw returning	Deep plowing	ATT		Planting green manure crops	Organic fertilizer
			Soil testing and formula fertilization	No-till seeding		
Four nearest neighbor matching	0.078** (0.0368)	0.117*** (0.0379)	0.063* (0.0316)	−0.013 (0.0269)	0.044 (0.0273)	0.025 (0.0320)
Kernel matching	0.063* (0.0338)	0.115*** (0.0350)	0.0540* (0.0299)	−0.006 (0.0244)	0.064** (0.0253)	0.034 (0.0290)
Radius matching	0.064* (0.0338)	0.116*** (0.0350)	0.056* (0.0298)	−0.006 (0.0244)	0.065** (0.0252)	0.035 (0.0289)
Mahalanobis matching	0.070*** (0.0230)	0.105*** (0.0273)	0.075*** (0.0238)	−0.020 (0.0250)	0.039* (0.0228)	0.042* (0.0243)

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

TABLE 9 Robustness test of replacement samples.

Statistics	Under 60 years old	Exclude samples from the Northeast region
ATT	0.211** (0.0992)	0.302*** (0.1095)
N	1,201	1,477

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

purchasing expenditure," and the village-level "proportion of connected households" and farmers' Internet usage, these variables are replaced with farmers' Internet usage, as shown in Table 11. The coefficients of the variables are all significantly positive.

Adjusting the model. Considering that the dependent variable ranges from 1 to 6, further regression is conducted using the ordered Probit model and Poisson model. The results show that the coefficient of Internet usage is significantly positive in both models, further confirming the above conclusions (Table 12).

5 Conclusion and policy recommendations

5.1 Conclusion

This paper examines the impact of Internet usage on farmers' land quality protection behavior in detail using propensity score matching and instrumental variable methods based on data from 1728 households surveyed in 14 provinces (autonomous regions) by the National Academy of Agricultural and Rural Development of China Agricultural University in January–February 2019. The main conclusion is that Internet usage significantly promotes farmers' land quality protection behavior. Based on four nearest neighbor matching, compared to farmers who do not use the Internet, Internet usage enables farmers to adopt 0.330 more land quality protection techniques. This conclusion remains robust after employing instrumental variable methods, adjusting the sample, variables, and model. Heterogeneity analysis indicates that Internet usage has a significantly positive effect on farmers with lower education levels and households in villages with guaranteed water sources. Moreover, the impact of the Internet is more pronounced for farmers who have received training, small-scale farmers, high-income farmers, households in poverty-stricken villages, and farmers in the northwest region. Expansion analysis shows that for land quality protection measures such as straw returning, deep tillage, soil testing and formula fertilization, and planting green manure crops, the ATT values are all significantly positive.

5.2 Policy recommendations

The above analysis indicates that Internet usage significantly promotes farmers' behavior in protecting land quality. This lays a solid theoretical and empirical foundation for China to implement the "Internet Plus Agriculture" action plan. This article primarily proposes policy recommendations in the following three aspects: First, increase the popularity of the Internet. Currently, there are still issues such as high costs and slow Internet speeds in rural areas, hindering Internet usage among farmers. Therefore, the government needs to increase funding and policy investment in rural Internet infrastructure to make it more accessible and faster for farmers, promoting equal access to telecommunications services. Additionally, enhance training for farmers on Internet usage to ensure they can both access and proficiently use the Internet. Second, policy formulation should take into account the heterogeneity among farmers, villages, and regions. As indicated by the analysis above, the utility of Internet usage varies among different types of farmers, villages, and regions. Therefore, policy-making should fully consider the differences among farmers and regions. For instance, emphasis should be placed on enhancing Internet usage skills for farmers with lower levels of education, while providing more in-depth training on Internet usage for those with higher levels of education. Third, enhance the promotion of measures for protecting farmland quality. As observed from the analysis above, while the adoption rate of stubble retention technology exceeds 50%, others remain below 50%. Therefore, the government should utilize various channels such as the Internet, agricultural machinery extension stations, and news media to disseminate information about the potential benefits of farmland quality protection measures. This will encourage more farmers to adopt these measures.

5.3 Discussion and limitations

The main conclusions of this study are consistent with existing research. Prior studies generally find that the Internet significantly enhances farmers' willingness to adopt green production technologies and engage in cultivated land protection practices. Our findings corroborate this pathway, further underscoring the crucial role of digital tools in promoting sustainable agricultural development. On

TABLE 10 Effect of Internet usage based on IV-2SLS on farmers' farmland quality protection behavior.

Variable	IV-2sls	
	The first stage	The second stage
Internet usage	-	0.451*** (0.1107)
Instrumental variable: Neighborhood Internet level	0.838*** (0.0361)	
Control variables	YES	YES
Province	YES	YES
Constant	−0.233** (0.1006)	1.509*** (0.4187)
Observations	1728	1728
Hausman endogeneity test	3.42*	
Cragg-Donald Wald F statistic	867.893	

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

TABLE 11 Robustness test for replacing core independent variables.

Variable	Replace core arguments		
Whether to publish online sales information	0.466*** (0.1245)		
Online purchase expenditure		0.055*** (0.0085)	
Proportion of online users			0.639*** (0.1059)
Control variables	YES	YES	
Province	YES	YES	
Constant	1.266*** (0.4316)	1.410*** (0.4137)	1.384*** (0.3977)
Observations	1,563	1,728	1,668
R-squared	0.2362	0.2260	0.2424

Due to missing data on "whether to publish online sales information" and the "proportion of households with Internet access in the village," the final sample size is 1,563 and 1,688, respectively. Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

TABLE 12 Robustness test for replacing core independent variables.

Variable	O probit model	Poisson model
Internet usage	0.267*** (0.0621)	0.145*** (0.0357)
Control variables	YES	YES
Province	YES	YES
Constant		0.226 (0.2391)
Observations	1728	1728
Pseudo R2	0.0768	0.0598

Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

this basis, this paper makes several extensions and innovations in terms of research objects, methods, and content: First, regarding research objects and data, most existing studies focus on a single region, which limits the representativeness of their data. By contrast, this study draws on 1,728 micro-level farmer survey samples covering 14 provinces (regions), thereby capturing regional and household heterogeneity in land protection behaviors. Second, in terms of methodology, while previous studies often employ Logit, Probit, or multiple regression models to identify causal relationships, this study applies propensity score matching (PSM) and instrumental variable (IV) methods. These approaches effectively mitigate sample selection bias and endogeneity issues, rendering the findings more robust and reliable. Finally, with respect to research content, this study not only examines the overall impact of Internet use on farmers' land protection behavior but also conducts heterogeneity analyses to reveal differentiated effects across farmer groups. In addition, through extended analyses, we refine the investigation into specific land quality protection practices—such as straw incorporation, deep tillage, soil testing and formulated fertilization, and green manure planting—demonstrating the unique value of Internet use in facilitating the adoption of targeted sustainable practices.

Finally, this study has the following limitations: First, data timeliness is insufficient. The data were collected between January and February in 2019. Considering the rapid development of digital infrastructure and Internet penetration in China in terms of both scale and technological forms in recent years, this time gap limits our ability to capture the most up-to-date dynamics of Internet use on farmer's cultivated land protection behaviors. Future research could incorporate the latest panel or follow-up survey data to better reflect the dynamic impacts of Internet use on farmer's land protection decisions.

Second, the mechanism analysis is lacking. Internet use may influence farmers' decisions through multiple channels, such as reducing information acquisition costs, improving technology diffusion, and strengthening policy transmission. However, this study does not systematically distinguish or test these mechanisms. Future research could introduce mediation effect models to more comprehensively uncover the mechanisms through which Internet use affects farmers' land protection behavior.

Third, the potential negative effects of Internet use have not been considered. This study mainly focuses on the positive effects of Internet use on farmers' land protection behavior, but negative effects may also exist. For instance, the spread of misleading information may induce short-term profit-seeking behaviors among farmers, which could undermine land protection efforts. Future research may adopt a broader framework to systematically examine both the positive and negative effects of Internet use, thereby providing more comprehensive policy implications.

Data availability statement

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

Ethics statement

Ethical review and approval were 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

XZ: Conceptualization, Writing – review & editing, Data curation, Funding acquisition, Writing – original draft, Resources, Formal analysis. YZ: Validation, Supervision, Methodology, Writing – review & editing, Conceptualization, Investigation, Writing – original draft. XG: Writing – review & editing, Data curation, Writing – original draft, Investigation, Methodology, Conceptualization.

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