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RESEARCH ARTICLE

Do digital agricultural technology extension services promote the adoption of organomineral fertilizer use? Evidence from China

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KEYWORDS

Digital agricultural technology extension services, farmer perceptions, organomineral fertilizer

HIGHLIGHTS

- Indiscriminate use of mineral fertilizers poses a significant threat to China's implementation of UN Sustainable Development Goal 2 (SDG-2).
- Farmers who use the digital agricultural technology extension services (DATES) had a 7.2%–10.2% increase in the probability of adopting organomineral fertilizer (OMF).
- DATES enhanced OMF adoption through benefit-cognitive effects and transaction-cost effects.
- Heterogeneity analysis indicated that DATES had a substantial influence on farmers with higher social capital and elevated economic status.

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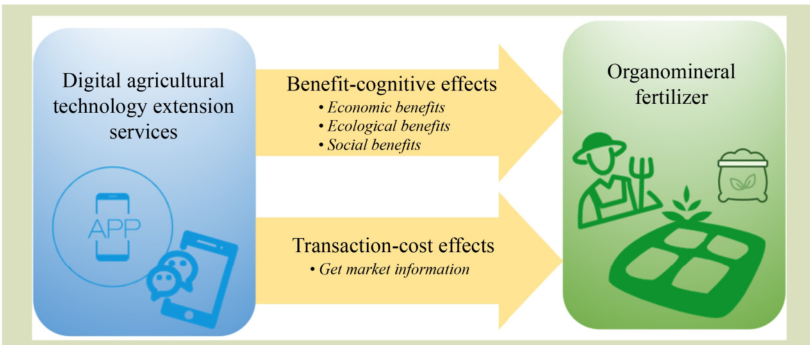
GRAPHICAL ABSTRACT



ABSTRACT

The development of Internet information technology has given digital agricultural technology extension services advantages over earlier agricultural technology extension models, rendering them more conducive to the pursuit of sustainable and environmentally friendly agricultural development. This study leveraged survey data from 1167 farmers in Shaanxi and Gansu Provinces and used the propensity score matching method to elucidate the impact and mechanism of the digital agricultural technology extension service on the adoption of organomineral fertilizer. The results indicate that farmers who had used digital agricultural technology extension services had a 7.2% to 10.2% increase in the probability of adopting organomineral fertilizer compared with their non-user counterparts. In addition, adoption intensity increased from 7.0% to 9.9%. Secondly, digital agricultural technology extension services indirectly influence farmer adoption behavior by shaping their perceptions of benefits and reducing transaction costs. Also, this study examined the heterogeneity in the adoption of organomineral fertilizer facilitated by digital agricultural technology extension services. The findings of this study provide policy recommendations for advancing the use of digital agricultural technology extension services and enhancing organomineral fertilize adoption rates of farmers.

1 Introduction

Mineral fertilizers are essential to ensuring food security and an efficient supply of essential agricultural products. However, the indiscriminate use of mineral fertilizers can potentially cause significant environmental problems, including soil nutrient imbalances, diminished fertility, water pollution[1] and deterioration in air quality[2]. These issues pose a significant threat to achieving food security and sustainable agriculture, as outlined in the UN Sustainable Development Goal 2 (to end hunger, achieve food security, improve nutrition, and promote sustainable agriculture).

Organomineral fertilizer (OMF) has been introduced and implemented for agricultural production in many developing countries to reduce the adverse effects of mineral fertilizers. This fertilizer is produced by combining organic materials, such as biosolids, livestock manure, crop residues, and food waste, with reduced quantities of mineral fertilizers, resulting in a balanced and nutrient-rich product. A large number of studies have shown that OMF can effectively improve soil fertility[3], increase crop yield and quality[4], and have positive significance for reducing environmental pollution and promoting sustainable agricultural development[5].

Given the significant benefits of OMF, the Chinese Government has developed policies to disseminate it[6]. However, owing to information asymmetry, small farmers, especially those in remote areas, may lack awareness of the importance of environmentally friendly production practices[7] and have a limited understanding of the technical requirements for organic fertilizer application[8]. This results in a low level of technology adoption. Therefore, it is necessary to reduce information asymmetry through modern information technology and encourage farmers to adopt it.

Digital agricultural technology extension services (DATES) use Internet platforms and media such as WeChat public accounts and applications to enable small farmers to access agricultural technology[9,10]. This approach overcomes the temporal and spatial limitations of existing agricultural technology extension modes[4], and helps reduce information asymmetry problems for small farmers. Norton and Alwang[9] found that extension services in developing countries are increasingly using diversified agricultural extension services driven by emerging information and communication technology services. One such example is the rice crop manager application promoted in the Philippines. In addition, the existing literature has shown that DATES can significantly improve agricultural production efficiency[11] and family farm income[12] and promote a range of environmentally friendly production behavior[13]. In a survey of 759 farmers in Shandong and Henan Provinces, Gao et al.[4] found that the impact of new agricultural technology promotion models on green technology adoption behavior of farmers has significant direct, spillover and distribution effects. Notably, Zheng et al.[14] found that DATES has different impacts on different agricultural green technologies, owing to the heterogeneity of technology characteristics. Therefore, the individual adoption of green technologies is worth discussing.

Given these findings, there are generally two limitations to existing studies that are relevant to our research. First, the literature usually reports the effects of DATES on green production technologies and only a few studies have focused on OMF adoption. Although it is theoretically believed that DATES can promote green agricultural production behavior[14], the heterogeneity of technological characteristics makes it important to study the adoption of individual technologies. Second, current research has yet to comprehensively investigate the mechanism, especially from the perspectives of benefit-cognitive effects and transaction-cost effects.

This study used cross-sectional survey data from 1167 households in the first and fifth major apple-producing provinces in China (Shaanxi and Gansu). We focus on the apple industry in China because it is the largest producer and consumer of apples globally, accounting for over 40% of global apple production[15]. However, only 3% of the apples produced in China are exported because of problems with pesticides and mineral fertilizer residues[16]. Influenced by the current view of many farmers that the more fertilizer that is applied, the higher the yield, Chinese fruit farmers are accustomed to applying large quantities of mineral fertilizers to achieve high apple yields, which has caused serious food safety, health and environmental problems. Excessive fertilizer application to cash crops is more serious[17,18]. Therefore, it is imperative to promote green, low-carbon, and sustainable development of China's apple sector.

Given the importance of the OMF in reducing fertilizer use and the significant role of DATES in promoting environmentally friendly production behavior, it is important to understand whether DATES can promote the adoption of OMF. We seek to make three important contributions to the existing literature. First, we use authentic micro-survey data to validate relevant inferences and enrich the current evidence on the impact of DATES on OMF adoption. Second, we examines the impact of benefit-cognitive effects and transaction-cost effects on green agricultural technology adoption. This also clarifies the intermediary role between DATES and farmer willingness to adopt OMF. Finally, we explore the heterogeneous effects of DATES among different groups. This classification provides valuable insights for government policymaking.

2 Theoretical analysis and research hypotheses

The concept of digital agriculture can be traced back to the FAO (2005) report, which mentioned agricultural extension services, dissemination of multimedia technology, and other related technical methods of transmitting information to promote agricultural development[19]. With the rapid development of the Internet and portable mobile terminals, farmers can obtain the necessary agricultural information and technical guidance through digital platforms such as WeChat official accounts, applets, and TikTok, without leaving home, forming a new agricultural technology promotion service model of the Internet plus new media[4,9]. From our perspective, we believe that if farmers actively receive agricultural technology information on their mobile phones, they are considered to have used DATES.

DATES transcends the temporal and spatial limitations of the existing extension modes, enabling information visualization and two-way communication[20]. These services help farmers overcome barriers to mastering technical information and expand their information acquisition channels, thus directly influencing their adoption of OMF[21]. In addition, technological advances, such as artificial intelligence and large-scale data analytics, have made DATES more intelligent[22]. They can now provide personalized technical advice and recommendations tailored to the needs and behavioral preferences of farmers[23], increasing their enthusiasm for adopting new technologies. Second, through Internet platforms, farmers can access accurate agricultural technology guidance, improve production efficiency, and enable professional, refined management[24], thus saving costs and influencing OMF adoption behavior of farmers. Based on the above analysis, this study proposes the following hypothesis.

H1: DATES can significantly promote adoption of OMF by farmers.

The application of organic fertilizers can effectively enhance soil organic matter in agricultural lands and maintain a stable fertilizer effect[2]. It is an effective means of reconciling economic benefits with environmental protection, enhancing farm production capacity, ensuring the quality and safety of agricultural products, and achieving green transformation and sustainable development of agriculture. This approach has significant economic, ecological and social benefits[3,4]. According to information search theory, the primary constraints on farmer production decisions are the costs of production and the availability of agricultural information[25]. DATES uses the Internet to expand avenues for information dissemination and acquisition, empowering farmers to access timely policy updates and gain insights into widespread scientific knowledge. This will enable farmers to understand the ecological repercussions of excessive mineral fertilizer use and the benefits of organic fertilizer application. Based on the above analysis, this study proposes the following hypotheses.

H1a: DATES can promote the adoption of OMF by improving farmer awareness of its economic benefits.

H1b: DATES can promote the adoption of OMF by improving farmer awareness of its ecological benefits.

H1c: DATES can promote the adoption of OMF by improving farmer awareness of its social benefits.

In the context of agricultural production, most farmers experience losses because of information asymmetry[3]. Using an Internet platform that facilitates information sharing, such as DATES, can enable farmers to access valuable insights from various channels. Active participation allows them to search for information tailored to their agricultural technology needs, enhancing information acquisition efficiency and reducing transaction costs[26]. Concurrently, information sharing can help farmers promptly adjust planting strategies and effectively minimize trial and error costs and risks, thereby increasing their enthusiasm for adopting OMF[27] (Fig. 1). Based on the preceding analysis, we propose the following hypothesis.

H1d: DATES can promote the adoption of OMF by reducing transaction costs.

China’s rural areas can be conceptualized as a strong relationship network, intertwined with a complex array of relationships, including those based on blood, kinship, geographical proximity and industrial ties. It can be observed that farmers with greater social capital tend to have more robust social networks and facilitate faster information circulation and dissemination[28]. Such networks facilitate the exchange of technology usage experiences and accumulation of technical knowledge, thereby reducing the cost of technology

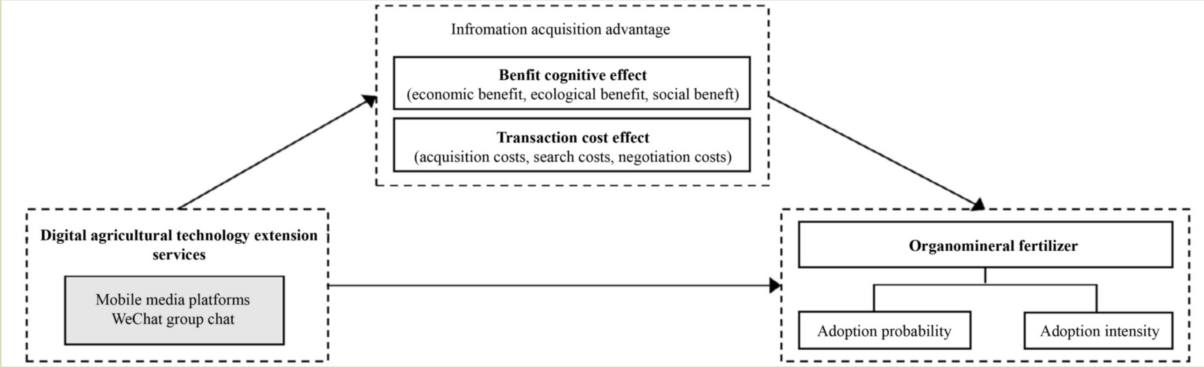


Fig. 1 Conceptual framework

learning and use and actively promoting the adoption of green technology[28,29]. The survey data used in this study were used to quantify the social capital abundance of farming families by the number of individuals who can provide financial assistance in times of need. This indicator accurately reflects the degree of closeness and trust between farmers, and their relatives, neighbors or friends. The more individuals a farmer can rely on for financial assistance during difficult times, the more stable their social resources become, facilitating the spread of policy information and the dissemination of technical knowledge, thereby encouraging the adoption of green technology. Based on this analysis, we propose Hypothesis 2a.

H2a: Social capital enhances the positive effect of DATES on OMF adoption.

Also, the implementation of OMF requires substantial economic support[6]. When farmers earn low incomes, their capacity to withstand adverse events is limited. Such farmers typically exhibit a pronounced aversion to risk and are either unable or unwilling to invest in modern agricultural practices. Conversely, farmers with more favorable economic conditions can better tolerate and recover from adverse events. Once they are made aware of the technology through DATES, they are more willing to take risks and be innovative[30]. As technological awareness increases, the probability of adopting the OMF also increases. This study divides farmers into two groups: those with better economic conditions and those with poorer financial conditions. This classification is based on whether their total annual income exceeds the sample mean. Based on this analysis, we proposed Hypothesis 2b.

H2b: Economic conditions enhance the positive impact of DATES on OMF adoption.

3 Methods and data

This section establishes a framework for evaluating the treatment effects associated with participation in DATES and illuminates the potential selection bias in the empirical evidence. The introduction of the propensity score matching (PSM) method effectively addresses the issue of sample selection bias that arises from observable factors.

3.1 Evaluation of the treatment effect

The binary variable R_i denotes farmer engagement with DATES, where R_i is the adoption of DATES, and conversely, R_i of 0 indicates no use of such services. The variables Y_{i1} and Y_{i0} represent the outcomes for adopters and non-adopters, respectively. The primary objective of this study was to investigate the magnitude of the treatment effect. Given that a sample farmer cannot simultaneously have both adoption and non-adoption status, there is the issue of missing data. To address the potential for selection bias due to both observable and unobservable factors, we used the PSM method[31].

3.2 Propensity score matching

In 1983, Rosenbaum and Rubin[32] introduced the PSM method, which has the advantage of controlling observable heterogeneous factors. It has been widely adopted by scholars and extensively used in research[30,33]. The fundamental concept of the PSM model involves constructing a counterfactual framework to minimize sample selection bias. This was accomplished by identifying a counterfactual control group that was similar to the treatment group. Within the PSM estimation framework, a binary choice model (specifically, a logit model) was used to estimate Eq. (1) and generate the propensity score for the sample farmers.

$$R_i^* = \gamma Z_i + \omega_i = \begin{cases} 1, \text{ if } R_i^* > 0 \\ 0, \text{ otherwise} \end{cases} \quad (1)$$

where, R_i is a binary variable indicating whether farmers use DATES, Z_i is an exogenous variable encapsulating the factors influencing farmer adoption of DATES, γ is an unknown parameter subject to estimation and ω_i is a random error item.

Subsequently, the sample farmers were matched based on propensity scores to ensure a balanced and comparable distribution between the two households. This process effectively mitigates the potential selection bias resulting from observable factors. Varieties matching methods have been developed to estimate the treatment effects. In this study, we used the most commonly used methods, namely nearest-neighbor matching, radius matching, and kernel-based matching. Nearest neighbor matching pairs each treated farmer with a control farmer based on the propensity score closest to that of the treated farmer. In contrast, radius matching pairs farmers within a specified tolerance (caliper) of propensity score differences using nearest-neighbor matching principles[15]. Kernel-based matching assigns weights to control group samples with propensity scores closer to those of the treatment group. To ensure the robustness of our estimation results, we used these three methods to mitigate estimation bias among the matching techniques, thereby bolstering the robustness of our research conclusions. Following the matching process, the mean and median differences served as measures to assess the balance between the treatment and control groups, providing insights into the equilibrium of data distribution between the two groups. Subsequently, we calculated the average treatment effect (ATE) by considering the OMF adoption decision of the treatment group, the OMF adoption decision of the control group and the treatment variable as:

$$\text{ATE} = E(Y_{i1} \mid R_i = 1) - E(Y_{i0} \mid R_i = 1) = E(Y_{i1} - Y_{i0} \mid R_i = 1) \quad (2)$$

3.3 Data

The data used in this study were derived from field surveys conducted by a research team on apple growers in Shaanxi and Gansu Provinces in March and June 2022. The selection of Shaanxi and Gansu Provinces as the research area was primarily based on the following considerations. First, Shaanxi and Gansu Provinces are the first and fifth largest apple-producing areas in China, respectively. In 2021, Shaanxi and Gansu accounted for 58.4% of China’s apple-planting area and 37.4% of its output. These figures objectively and genuinely reflect the production status of Chinese apple farmers. Second, Shaanxi and Gansu Provinces are central agricultural provinces in China that use substantial quantities of mineral fertilizers. According to statistics from the Ministry of Agriculture and Rural Affairs of China, the amount of elemental nitrogen applied of apple orchards in China has increased from 375 kg·ka^{-1} in 2008 to 490 kg·ka^{-1} in 2014. The amount of nitrogen applied in apple-producing areas in Gansu and Shaanxi Provinces also exceeded the national average, reaching 577 and 558 kg·ka^{-1}, respectively. Third, the sample encompasses both OMF policy pilots and general counties. A particular hierarchy can be observed in the intensity of supporting policies and the activities of farmers adopting green technologies. These conditions render Shaanxi and Gansu Provinces optimal samples for analyzing the impact and heterogeneity of DATES on OMF adoption.

The study was conducted in two stages. The initial stage of the investigation involved a pre-survey conducted in December 2021. This involved the random selection of 20 farmers from each province for household interviews. The objective of this preliminary investigation was to gain insights into the adoption of DATES and the adoption of OMF. The preliminary survey results were used to refine the questionnaire. The second stage was a formal survey administered to nearly 20 postgraduate students who had received professional training in questionnaire administration. To ensure the representativeness of the survey sample, a multistage stratified sampling approach was used, with counties in the Shaanxi and Gansu Provinces selected randomly from a pool of high-producing apple-producing counties. Towns within these counties were randomly selected, and villages within towns were then randomly selected from each county. Finally, farmers were randomly selected from each village. A total of 1302 questionnaires were distributed and screened according to these three criteria. (1) Samples with significant missing data, defined as responses to less than 60% of the questionnaire questions, were eliminated. (2) Samples with inconsistent information or logical contradictions were eliminated. (3) Samples with zero apple business areas were eliminated. The final number of valid samples was 1167, representing a recovery rate of 89.6%. Table 1 shows the distribution of the sample farmers.

Table 2 presents the characteristics of the sampled farmers. The respondents were predominantly middle-aged and older men with junior middle school educational levels. In particular, 70.2% of the respondents were over 50, and 81.5% had an educational level below a junior middle school. Also, 72.2% of the households had a total income of less than 100,000 yuan. For most families, the apple-planting area was between 2 and 6

Table 1 Sample distribution

Province	City	County	Number of farmers	Proportion (%)
Shaanxi	Yan'an, Weinan, Xianyang	Baota, Luochuan, Baishui, Xunyi	560	48.0
Gansu	Pingliang, Qingyang	Jingning, Qingcheng, Xifeng, Zhuanglang	607	52.0

Table 2 Basic characteristics of sample farmers

Feature	Classification	Proportion (%)	Feature	Classification	Proportion (%)
Gender	Male	94.1	Total Income	⩽ 50,000 yuan	39.5
	Female	5.90		(50,000, 100,000]	32.7
Age	⩽ 40	7.20		⩾ 100,000 yuan	27.8
	(40, 50]	22.6		⩽ 2 ha	32.9
	(50, 60]	44.3	Total apple area	(5, 15]	55.3
	⩾ 60	25.9		⩾ 6 ha	11.8
Educational level	Primary school and below	39.2		⩽ 2	65.2
	Junior middle school	42.3	Number of farm workers	(2, 4]	32.7
	High school and above	18.5		⩾ 4	2.10

ha, accounting for 55.2% of the total area. Additionally, 65.3% of respondents had fewer than three laborers. In summary, most respondents were older, less educated, had smaller cultivated land areas, and had lower income levels. This reflects the development status of China's agriculture and rural areas and offers a representative sample.

3.4 Variables selection and descriptive statistics

The dependent variable in this study was the adoption of OMF by farmers. The OMF application mode promoted in the apple industry is primarily classified into four categories: (1) organic fertilizer plus formula fertilizer, (2) fruit-biogas-livestock, (3) organic fertilizer plus water and fertilizer integration, and (4) natural grass plus green manure. Farmers adopting any of the four modes are assigned a value of 1, and those who do not adopt any are assigned a value of 0. The adoption intensity of the OMF was measured as the proportion of apple orchard areas using OMF relative to the total apple planting area.

The core independent variable was the digital agricultural technology extension services. This article draws on and summarizes definitions of DATES from previous research[4,9,10]. The hypothesis is that farmers who obtain agricultural technology extension service information through communication equipment are considered to be using DATES. We used the questionnaire, which asked if farmers browse information related to agricultural planting knowledge and technology-related information on their mobile phones. The variable was assigned a value of 1 if farmers use mobile media platforms to obtain agricultural technology information; otherwise, it was assigned a value of 0. Additionally, the study included the data for whether farmers joined in chats on agricultural production exchange consultation and other aspects and the number of times farmers use mobile phones to browse agricultural planting knowledge and technology-related information to conduct a robustness test on the baseline estimation results.

Table 3 presents the definitions and descriptive statistics of the variables used in the empirical analysis. In the sample, the overall adoption rate of OMF was about 74.3%, with an adoption intensity of 72.9%. About 48.4% of the surveyed farmers also used DATES.

In the propensity score matching process, covariates that influence DATES and OMF were included in the propensity score model as control variables whenever possible. Therefore, it was necessary to ensure that these variables were as close as possible to the exogenous variables. Previous studies have demonstrated that several factors influence farmer willingness to adopt DATES and OMF. These include farmer characteristics[4,6], household characteristics[7,18], and essential village characteristics[34]. Accordingly, this study selected age, gender, educational level, party membership, risk attitude and participation in technical training as individual characteristics.

Table 3 Descriptive statistics of the variables

Variables	Definitions	Mean	SD
Dependent variables			
Adoption of OMF	Yes = 1, No = 0	0.743	0.437
OMF adoption intensity	Apple acreage using OMF divided by total apple acreage	0.729	0.435
Independent variable			
Participation in DATES	Farmers browse information related to agriculture planting knowledge and technology-related information on their mobile phones: Yes = 1, No = 0	0.484	0.500
Instrumental variable			
Average use of DATES by other sample farmer households in the village	The proportion of other farmers in the sample village who access information related to agriculture planting knowledge and technology-related information on their mobile phones	0.508	0.043
Individual controls			
Age	Actual age of respondents	55.0	9.43
Gender	Male = 1, female = 0	0.941	0.236
Educational level	Elementary school = 1, middle school and high school = 2, high school and above = 3	1.76	0.698
Party membership	Yes = 1, No = 0	0.144	0.351
Technical training	Yes = 1, No = 0	0.660	0.474
Risk aversion	Percentage of times the low-risk option was selected across five games	0.820	0.384
Household controls			
Cooperative identity	Yes = 1, No = 0	0.206	0.404
Total apple area	Apple planting area of respondents' households in 2022	9.59	9.61
Concentration of apples	Respondents self-rated: very scattered = 1, relatively scattered = 2, average = 3, relatively concentrated = 4, very concentrated = 5	3.45	1.16
Apple growing years	Duration of apple planting in the households of respondents in 2022	20.3	9.82
Orchard topography	Flat land = 1, sloping land = 2, terraces = 3, tableland = 4, mountain plateau = 5	1.53	0.930
Disaster damage	Whether the critical apple growth period of respondents' homes in the past five years was affected by climate disasters	0.779	0.415
Ln income	Log value of total household income in 2022 in yuan	10.9	0.941
Village controls			
Village economic level	Very poor = 1, poor = 2, average = 3, good = 4, very good = 5	0.300	0.458
Express logistics convenience	Very inconvenient = 1, inconvenient = 2, general = 3,more convenient = 4, very convenient = 5	0.685	0.465
Shaanxi Province	Whether the respondent belongs to Shaanxi Province: Yes = 1, no = 0	0.480	0.500
Channel variables			
Economic benefits	This technology can help improve family farming income: totally disagree = 1, relatively disagree = 2, generally = 3, relatively agree = 4, completely agree = 5	3.77	0.999
Ecological benefits	This technology can reduce the pollution of fertilizer to the environment: totally disagree = 1, relatively disagree = 2, generally = 3, relatively agree = 4, completely agree = 5	3.77	1.01
Social benefits	This technology can improve the whole rural ecological environment: totally disagree = 1, relatively disagree = 2, generally = 3, relatively agree = 4, completely agree = 5	3.89	1.04
Information acquisition efficiency	Getting information about the apple market is easy: very difficult = 1, relatively difficult = 2, average = 3, easy = 4, very easy = 5	2.91	1.25

Note: OMF, organomineral fertilizer; DATES, digital agricultural technology extension services.

Of the household characteristics, participation in cooperatives[34], total household income, apple orchard area, apple orchard concentration, apple orchard topography, years of apple planting and the number of adverse events in the previous 5 years were selected as the control variables included in the model. Additionally, the economic level of village residents, logistics conditions and province were selected and included as village-level control variables. Previous studies have indicated that soil organic carbon and total nitrogen storage in orchards on steep slopes and hills is comparatively lower than that on relatively flat terrain[35]. Consequently, it can be surmised that the topographical characteristics of orchards will exert a direct influence on the use of organic fertilizers. This study used a 1–5 ordinal variable to represent the steepness of the terrain. The survey revealed that farmers affected by natural disasters are generally unenthusiastic about adopting green and low-carbon technologies, consistent with the results of Shi and Lai[35]. The number of adverse events in this study refers to natural events such as droughts, floods, windstorms, snowstorms, frosts and high-temperature damage over the previous 5 years. To eliminate the impact of natural disaster shocks on the OMF adoption rate, it was necessary to incorporate this variable into the control variable.

As illustrated in Table 3, the proportion of party members among the surveyed farmers was effectively inconsequential. About 66% of respondents had received technical training. The average duration of planting is about 20 years, with the orchard area measuring about 3.8 ha, primarily on flat terrain. By 2022, the total household income of the surveyed fruit farmers was about 57,000 yuan. The surveyed farmers perceived the economic status of their village to be average while emphasizing the relative convenience of transportation and logistics.

4 Results and discussion

We used propensity scores derived from a logit model to ascertain participation in DATES. We then conducted PSM estimations to determine the effects of treatment on the primary outcome variables. Also, we investigate the potential mechanisms and heterogeneity through which participation in DATES may influence OMF.

4.1 Estimation of influencing factors on DATES participation

To assemble a matched sample of farmers who participate in DATES with those who do not, it is imperative to conduct a regression analysis of the conditional probability fitting values associated with farmers adopting DATES. The dependent variable was the use of DATES, while whereas the independent variables were personal and family characteristics. A logit model was used to establish a propensity score for each variable. Table 4 presents the results of this analysis.

Several factors were identified as significantly influencing farmer adoption of DATES. These factors included age, educational level, cooperative identity, party membership, risk aversion, orchard topography and past disaster experiences. Notably, party members had greater human capital quality compared with non-party members, rendering them more adept at using the Internet for information acquisition[34]. The negative impact of age, with a significance level of 1%, indicates that older individuals are less inclined to acquire agricultural technology knowledge via the Internet. This may be due to the preference for interpersonal interactions for information retrieval. This observation was consistent with that of Ma and Abdulai.[36]. A significant positive correlation at the 1% level indicates that higher levels of education enhance farmer willingness to use the Internet. As educational levels increase, farmers begin to recognize the importance of online information channels, a trend previously documented in previous studies[37]. Risk-averse farmers are more inclined to use the Internet for agricultural technology knowledge, driven by their cautious approach to production decisions and role of the Internet in mitigating risk costs[38]. Unlike other findings that reveal a significant effect of the apple-planting scale on participation in DATES[4], our results indicate that the total apple area has no impact on individual DATES participation. This may be because the information available on mobile phones is not sufficiently systematic or detailed to meet the needs of large-scale farmers. For these farmers, receiving specific and targeted guidance directly from trusted experts is more reliable and effective than obtaining fragmented information via mobile phones. Cooperative membership is associated with greater exposure to new modes of agricultural technology extensions. Also, the terrain of the orchards had a positive and significant impact on the farmer adoption of DATES. The challenging conditions of steep terrain orchards, which are characterized by poor soil quality and irrigation difficulties, necessitate the use of advanced agricultural technologies. The motivation to increase profits drives farmers to use the Internet as a source of information to address practical planting challenges.

4.2 Propensity score matching estimation for the effects of DATES

4.2.1 Common support domains and balance checks

The efficacy of the PSM method depends on the satisfaction of

Table 4 Logit estimation results for participation in DATES

Variable	Coefficient	Standard error	*p*-value
Age	−0.026	0.007	0.000***
Gender	0.000	0.263	0.999
Educational level	0.336	0.093	0.000***
Cooperative identity	−0.287	0.156	0.066*
Party membership	0.552	0.184	0.003***
Technical training	0.166	0.131	0.206
Risk aversion	−0.436	0.162	0.007***
Total apple area	0.000	0.006	0.974
Concentration of apples	−0.068	0.054	0.211
Apple growing years	0.003	0.007	0.697
Orchard topography	0.118	0.069	0.084*
Disaster damage	0.377	0.152	0.013**
Village economic level	0.133	0.134	0.321
Express logistics convenience	0.097	0.133	0.468
Ln income (in yuan)	0.037	0.066	0.570
Shaanxi Province	−0.198	0.133	0.137
Cons	0.295	0.922	0.749
LR $chi^2(12)$		87.0***	
Pseudo-R^2		0.0538	
Sample size		1167	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

two fundamental prerequisites. The first prerequisite is the common support hypothesis, which stipulates that the propensity scores of the treatment and control groups should encompass a broad common support domain. Figure 2 shows the outcomes of the kernel-based matching test, which revealed 14 samples outside the common support domain and 1153 successfully matched samples. The treatment group had a loss of 11 observations, whereas the control group experienced a loss of three observations. Notably, the common support domain retained a substantial number of samples from the treatment group, indicating a high-quality matching process.

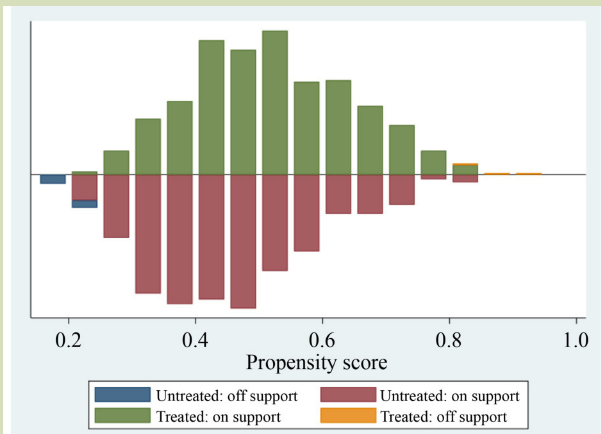


Fig. 2 Propensity score distribution and common support for propensity score matching.

Another prerequisite for implementing PSM is the balance assumption, which stipulates the absence of systematic differences in each matching variable between the treatment and control groups following matching. Different matching methods result in varying degrees of sample loss. To enhance the robustness of the results, this study used a range of matching methods, including nearest-neighbor matching, radius matching, and kernel-based matching. In addition, the overall balance was evaluated following the criteria established in previous studies[39], and the detailed results are presented in Table 5. The mean and median deviations of the post-matching covariates were significantly reduced compared with their pre-matching values. The p-value from the likelihood ratio test

Table 5 Balance test results for explanatory variables before and after matching

Matching method	Pseudo-R^2	LR chi^2	P > chi^2	Mean bias (%)	Median bias (%)
Before matching	0.054	87.0	0.000	13.2	13.8
Kernel-based matching	0.002	3.42	1.000	2.40	1.80
Nearest neighbor matching	0.010	15.3	0.502	5.30	5.10
Radius matching	0.009	14.4	0.570	4.50	3.10

Note: The controls included age, gender, educational level, party membership, technical training, risk aversion, cooperative identity, total apple area, the concentration of apples, apple growing years, orchard topography, disaster damage, ln income, village economic level, express logistics convenience, and Shaanxi Province.

indicates that the difference in the means of the covariates between the two sample groups was no longer statistically significant after matching. This analysis demonstrates that PSM effectively diminishes the differences in explanatory variables between the treatment and control groups, thereby achieving a well-balanced data set. Table S1 uses kernel-based matching to demonstrate no statistically significant differences in the covariates between users and non-users of digital agricultural technology extension services in the matched sample. This indicates that the bias introduced by the selection factors was effectively controlled.

4.2.2 Treatment effect from propensity score matching

To enhance the robustness of the estimation results, this study used three matching methods to assess the average treatment effect of DATES on OMF adoption decisions. The findings demonstrate that the influence consistently aligns with the overall trend, despite variations in the results obtained using different matching methods. Also, the average treatment effects successfully pass the significance test, thereby confirming the robustness of the estimation results.

Table 6 reveals that mitigating sample selection bias enhances the understanding of DATES usage by farmers and its impact on OMF adoption. From a counterfactual perspective, if farmers who are deemed to use DATES do not actually use the service, their probability of adopting OMF ranged from 0.681 to 0.711. However, the probability of adoption increased to 0.783 with the introduction of DATES, representing a growth of 0.072–0.102, or a 10.3%–15.0% growth rate. For the intensity of OMF adoption (Table 7), the average treatment effect ranges from 0.070 to 0.099. This indicates that, regardless of other influencing factors, farmers who had already adopted this technology and further engaged with DATES were likely to have had an increase in adoption levels, from 7.0% to 9.9%. This indicates the capacity of DATES to enhance farmer enthusiasm for using green production behavior, thereby facilitating the expansion of the scale of adoption[40]. These outcomes contribute to the dual objectives of economic development and ecological protection.

4.3 Channel analysis

The preceding analysis of the results indicates a positive and statistically significant influence of DATES on OMF adoption behavior of farmers. Nevertheless, the precise mechanism by which DATES exerts this effect remains to be elucidated and empirically validated. This study used kernel-based matching as a case study to elucidate its specific mechanism by examining it from the perspective of benefit cognition and the costs associated with information acquisition.

The integration of the Internet with conventional agricultural

Table 6 Average treatment effect of DATES on OMF adoption probability

Matching method	Treatment group mean	Control group mean	ATT	Increase ratio (%)
Before matching	0.784	0.704	0.080***	11.4%
Kernel-based matching	0.783	0.711	0.072***	10.3%
Nearest neighbor matching	0.783	0.681	0.102***	15.0%
Radius matching	0.783	0.709	0.074***	10.4%

Note: The calculation formula for the increase ratio is: increase ratio = ATT/mean of the control group × 100%. The controls included age, gender, educational level, party membership, technical training, risk aversion, cooperative identity, total apple area, concentration of apples, apple growing years, orchard topography, disaster damage, ln income, village economic level, express logistics convenience, and Shaanxi Province. *** $p < 0.01$.

Table 7 Average treatment effect of DATES on OMF adoption intensity

Matching method	Treatment group mean	Control group mean	ATT	Increase ratio (%)
Before matching	0.771	0.690	0.081^{***}	11.7%
Kernel-based matching	0.770	0.700	0.070^{***}	10.0%
Nearest neighbor matching	0.770	0.671	0.099^{***}	14.8%
Radius matching	0.770	0.694	0.076^{***}	11.0%

Note: The calculation formula for the increase ratio is: increase ratio = ATT/mean of the control group × 100%. The controls included age, gender, educational level, party membership, technical training, risk aversion, cooperative identity, total apple area, concentration of apples, apple growing years, orchard topography, disaster damage, ln income, village economic level, express logistics convenience, and Shaanxi (province). *** $p < 0.01$.

technology extension services in DATES enhances the efficiency of information transmission and facilitates a more convenient and rapid process. This combination expedites the accumulation of knowledge regarding green production behavior among farmers, concomitantly enhancing their understanding of the ecological, economic and social values associated with organomineral fertilizers[41,42]. In theory, DATES has the potential to enhance farmer awareness of the ecological, economic and social benefits associated with the adoption of OMF. The regression results presented in Table 8 are consistent with these hypotheses. Active engagement in DATES has been demonstrated to have a substantial and positive influence on perceptions of ecological, economic and social values. Specifically, there has been an improvement of 14.7%, 15.7%, and 11.7%, respectively. This finding is consistent with the existing studies in which farmer cognition had significant mediating effects on farmer behavior[6].

The Internet is an efficient and expeditious channel for disseminating information. In the context of implementing green production technologies, farmers can use DATES to connect with broader agricultural communities. This facilitates seamless access to agricultural production and management knowledge, thereby alleviating information constraints and reducing the associated costs. Consequently, DATES is pivotal to facilitating the adoption of organomineral fertilizers by reducing the costs associated with acquiring information. The regression results presented in Table 8 shows a significant positive effect of the use of DATES by farmers on the availability of agricultural information. This evidence supports the assertion that DATES indeed has a pivotal role in promoting OMF adoption by reducing information acquisition costs.

4.4 Heterogeneity analysis

The preceding analysis demonstrates the beneficial role of DATES in facilitating the adoption of OMF by farmers. However, it is crucial to recognize that this conclusion reflects the average effect observed across the sample. As independent entities, the use of agricultural production technology by farmers is subject to various external and internal factors. External influences stem from the broader environment, whereas internal influences arise from the diverse characteristics of farmers themselves. In other words, for farmers with different characteristics, arising from differences in their comparative advantages, subjective cognition and behavioral capabilities, it is relatively simple to differentiate their adoption behavior. This study aims to analyze differences in the abundance of family social capital and family economic

Table 8 Propensity score matching regression results for the effects of DATES on potential channels

Variables	Ecological value	Economic value	Social value	Information acquisition cost
ATT	0.147^{*} (0.062)	0.157^{**} (0.062)	0.117^{*} (0.065)	0.209^{***} (0.078)
Controls	YES	YES	YES	YES
Balancing property satisfied	YES	YES	YES	YES
Common support imposed	YES	YES	YES	YES
N	1167	1167	1167	1167

Note: The calculation formula for the increase ratio is: increase ratio = ATT/mean of the control group × 100%. The controls included age, gender, educational level, party membership, technical training, risk aversion, cooperative identity, total apple area, concentration of apples, apple growing years, orchard topography, disaster damage, ln income, village economic level, express logistics convenience, and Shaanxi (province). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

conditions to more clearly depict the heterogeneous effects of DATES in various contexts.

4.4.1 Social capital

This study categorized the sample into high- and low-social capital groups based on the average number of individuals capable of providing financial assistance during difficult circumstances. Group regression analyses were conducted to investigate the nuanced impact of social capital on the research variables in greater detail. The results in Table 9 indicate that, in samples with high social capital, the coefficient of DATES is significantly positive at the 1% level. However, this coefficient failed to attain statistical significance in the samples marked by low social capital. The observed significance implies that DATES exerts a more pronounced influence on OMF adoption decisions of farmers with elevated social capital, aligning with the anticipated outcomes. The richness of social network relationships may serve to mitigate information asymmetry and facilitate the dissemination of information.

4.4.2 Economic level

In this study, the economic status of farming families was evaluated using an annual household income index. The economic level was considered superior when its value exceeded the sample mean. The findings indicate a notable positive impact of DATES on OMF adoption behavior, of farmers particularly in the context of more favorable economic conditions. Conversely, no statistically significant effect was observed for farmers in less affluent economic circumstances. The results in Table 9 align with expectations, indicating that farmers from economically advantaged families have greater investment capacity and risk resilience, making them more predisposed to adopting OMF. Conversely, farmers facing economic challenges had limited investment capabilities and a leaning toward risk aversion, which makes them more inclined to use the common fertilizer application methods.

4.5 Robustness check

4.5.1 Replace explanatory variables

To avoid bias in selecting core explanatory variables, this paper used the survey results of two variables that recored if farmers participated in agricultural production discussions in WeChat group chats and the frequency with which farmers used mobile phones to browse information related to agricultural planting and technology[43]. These variables were used to measure DATES and conduct a robustness test on the benchmark regression results. Table 10 indicates that active participation in agricultural production communication group chats and browsing information related to agricultural production and technology have significant impacts on adoption behavior and OMF adoption intensity. This may be attributed to the fact that active participation in agricultural production-related group chats can effectively promote information exchange among farmers, thereby enhancing their adoption level. Peer effects are also a significant factor in this regard. Active use of mobile phones by farmers to access information on agricultural planting techniques and related technologies can effectively address information asymmetry and enhance their understanding of green agricultural behavior. This, in turn, significantly promotes the adoption of OMF. In conclusion, even after replacing the definitions of the core explanatory variables, DATES continued to exert a significant influence on farmer adoption behavior and intensity concerning OMF. These findings reinforce the robustness of the initial conclusions drawn from the benchmark regression results presented in this article.

Table 9 DATES affects on OMF adoption by farmers: differences based on social capital and economic level

Category name	Treatment group mean	Control group mean	ATT	Standard error
Social capital				
High social capital	0.813	0.682	0.131***	0.048
Low social capital	0.747	0.715	0.032	0.034
Economic level				
Better economic	0.807	0.698	0.109***	0.034
Poor economic	0.741	0.749	−0.007	0.048

Note: The calculation formula for the increase ratio is: increase ratio = ATT/mean of the control group × 100%. The controls included age, gender, educational level, party membership, technical training, risk aversion, cooperative identity, total apple area, concentration of apples, apple growing years, orchard topography, disaster damage, ln income, village economic level, express logistics convenience, and Shaanxi (province). *** $p < 0.01$.

Table 10 Average treatment effect results of DATES on OMF adoption after replacing explanatory variables

Variables	Whether to adopt OMF	OMF adoption intensity	Whether to adopt OMF	OMF adoption intensity
Participate in WeChat group chats	0.070^{**} (0.031)	0.054^{*} (0.031)		
Browse agricultural technology-related information times			0.195^{**} (0.088)	0.165^{*} (0.087)
Controls	YES	YES	YES	YES
N	1167	1167	1167	1167

Note: The controls included age, gender, educational level, party membership, technical training, risk aversion, cooperative identity, total apple area, the concentration of apples, apple growing years, orchard topography, disaster damage, ln income, village economic level, express logistics convenience, Shaanxi (province). ** $p < 0.05$, * $p < 0.1$. Standard errors are presented in parentheses.

4.5.2 Endogenous switching regression model test

The PSM method effectively addresses sample selection bias arising from observable variables. However, the presence of unobservable variables may introduce bias that is not readily apparent. This study used the endogenous switching regression (ESR) method to conduct a robustness test on all sample farmers to correct endogeneity problems related to unobservable factors. This study drew inspiration from the methodology of Weng et al.[43], which uses the average use of digital agricultural technology extension by other sample farming households in the village as an instrumental variable to determine farmer adoption of DATES. The average use of DATES by other sample farming households in the village is determined by the proportion of farmers who access information related to agricultural planting and technology-related information on their mobile phones. The rural society of China is an acquaintance-based society. Agricultural production information and technology often have spillover effects, allowing farmers to easily imitate and learn from each other. This implies that the adoption behavior of one farmer can influence that of others, creating a demonstration effect within the village[4]. Therefore, it can be assumed that farmers who do not use DATES may be encouraged to adopt it based on the recommendations of other farmers in the village. These two parameters are highly correlated. Also, given the decision-making independence among farmers, the use of DATES by other farmers will not directly influence the adoption of OMF by farmers, thereby satisfying the exogeneity condition. However, some studies have raised concerns that this type of instrumental variable may not fully satisfy the exclusivity restriction. Consequently, it should be interpreted with caution and considered as suggestive evidence rather than definitive proof.

The results of the estimation of the factors influencing the decision to adopt OMF and the intensity of adoption are presented in Table 11. First, the estimated coefficient of the instrumental variable (the average use of DATES by other sample farming households in the village) was statistically significant at the 1% level, with a positive response aligned with expectations. This indicates that farmers in villages with a large number of DATES users are more likely to use the Internet to access technical agricultural information. Second, the Cragg-Donald Wald *F*-statistic, with a value of 14.3, leads to the rejection of the null hypothesis of weak instrumental variables, thereby confirming the validity of the instrumental variables used in the analysis. Also, the Wald test values for the independence of the two-stage equation, at 5.59 and 16.0, respectively, indicate that the assumption that the choice and result equations are independent is rejected at the 1% and 10% levels. This rejection indicates that unobservable factors influence farmer participation in DATES and their decisions on OMF adoption, thereby giving rise to endogeneity issues. The error correlation coefficient also demonstrated statistical significance, indicating the presence of self-selection in the adoption of DATES. Consequently, the ESR model is appropriate for addressing this endogeneity problem.

The results presented in Table 12 demonstrate that, even after applying the ESR model to address sample selection bias, the use of DATES continues to significantly influence decisions of farmers to adopt OMF. ATT for OMF adoption behavior was 0.370, while the intensity of ATT adoption was 0.252, both of which exceeded the 5% and 1% significance levels. This indicates that farmers who engage in DATES are 37% more likely to adopt OMF than those who do not. Also, those who have used DATES had 25.2% higher adoption intensity than those who have not adopted this technology. The consistent affirmation of these outcomes by the ESR model underscores the substantial and positive impact of DATES participation on adoption of OMF by farmers.

4.5.3 Double-hurdle model test

To enhance the robustness of the results, a double-hurdle model was used to test the experimental data. Table 13 presents

Table 11 Estimation of DATES participation in OMF adoption behavior

Variables	Whether to adopt OMF			OMF adoption intensity		
	DATES	= 1	= 0	DATES	= 1	= 0
Average use of DATES by other sample farmer households in the village	9.87*** (2.64)			8.27*** (1.26)		
Age	−0.012*** (0.005)	−0.011* (0.005)	0.004 (0.007)	−0.011*** (0.004)	−0.000 (0.002)	−0.001 (0.002)
Gender	0.086 (0.163)	−0.020 (0.194)	0.403* (0.219)	0.078 (0.162)	−0.047 (0.064)	0.165*** (0.080)
Educational level	0.199*** (0.057)	0.145** (0.074)	−0.031 (0.097)	0.194*** (0.058)	0.006 (0.026)	−0.003 (0.028)
Cooperative identity	−0.115* (0.096)	−0.108 (0.114)	0.426*** (0.141)	−0.101 (0.097)	0.027 (0.041)	0.105*** (0.042)
Party membership	0.318*** (0.115)	0.472*** (0.126)	−0.426*** (0.176)	0.320*** (0.113)	0.108*** (0.039)	−0.122*** (0.061)
Technical training	0.173 (0.081)	−0.015 (0.103)	0.341 (0.132)	0121 (0.081)	−0.032 (0.037)	0.106*** (0.039)
Risk aversion	−0.212*** (0.100)	−0.300*** (0.115)	−0.294 (0.215)	−0.252 (0.100)	−0.057 (0.040)	−0.116*** (0.049)
Total apple area	0.002 (0.004)	0.004 (0.005)	0.027*** (0.011)	0.002 (0.004)	−0.001 (0.002)	0.002* (0.001)
Concentration of apples	−0.029 (0.033)	−0.051 (0.040)	−0.039 (0.052)	−0.025 (0.033)	−0.007 (0.015)	−0.013 (0.015)
Apple growing years	−0.004 (0.004)	0.005 (0.005)	−0.008 (0.006)	−0.002 (0.004)	0.001 (0.002)	−0.002 (0.002)
Orchard topography	0.071* (0.042)	0.118*** (0.051)	0.130 (0.080)	0.075** (0.042)	0.039*** (0.018)	0.033* (0.018)
Disaster damage	0.263** (0.093)	0.006 (0.156)	0.004 (0.141)	0.268*** (0.094)	−0.063 (0.042)	0.035 (0.042)
Village economy level	0.060 (0.082)	0.039 (0.097)	−0.059 (0.120)	0.060 (0.083)	0.001 (0.036)	−0.026 (0.039)
Express logistics convenience	0.051 (0.083)	0.051 (0.096)	−0.017 (0.115)	0.057 (0.083)	0.028 (0.037)	0.020 (0.038)
Ln income	0.046 (0.040)	−0.001 (0.050)	0.042 (0.056)	0.039 (0.040)	−0.006 (0.019)	0.015 (0.019)
Shaanxi Province	−0.906 (0.227)	0.282 (0.188)	0.831*** (0.150)	−0.900 (0.225)	0.192*** (0.036)	0.280*** (0.039)
Cons	−0.869 (0.650)	0.056 (0.715)	−1.36 (0.819)	−0.989 (0.652)	0.759*** (0.266)	0.223 (0.282)
ahrho1		1.89** (0.887)			0.500*** (0.056)	
rho1		1.23*** (0.156)			0.225*** (0.089)	
ahrho0			−0.601 (0.507)			0.498*** (0.028)
rho0			−0.530* (0.322)			−0.298*** (0.092)
LR test	5.59*			16.0***		
Cragg-Donald Wald F statistic	14.3			14.3		
N	1167	1167	1167	1167	1167	1167

Note: ahrho1, ahrho0, rho1, rho0 are the correlation coefficients of the error terms of the simultaneous estimation of the equations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard error in parentheses (under coefficients).

Table 12 Average treatment effect of DATES on OMF adoption behavior: Endogenous Switching Regression model

Variables	Whether to adopt OMF	OMF adoption intensity
ATT	0.370^{**} (0.183)	0.252^{***} (0.009)
Controls	YES	YES
N	565	565

Note: ATT is average treatment effect.The controls included age, gender, educational level, party membership, technical training, risk aversion, cooperative identity, total apple area, concentration of apples, apple growing years, orchard topography, disaster damage, ln income, village economic level, express logistics convenience, and Shaanxi (province). *** $p < 0.01$, ** $p < 0.05$.

Table 13 Double-hurdle model results of DATES on OMF adoption behavior

Variables	Hurdle 1: Whether to adopt OMF	Hurdle 2: OMF adoption intensity
Participate in DATES (yes = 1)	0.322^{***} (0.087)	0.020^{***} (0.007)
Age	−0.002 (0.005)	−0.000 (0.000)
Gender	0.118 (0.173)	−0.002 (0.016)
Educational level	0.036 (0.063)	−0.004 (0.005)
Cooperative identity	0.201^{*} (0.110)	0.016^{*} (0.009)
Party membership	0.077 (0.130)	−0.001 (0.010)
Technical training	0.145 (0.088)	−0.005 (0.008)
Risk aversion	-0.290^{**} (0.116)	−0.002 (0.009)
Total apple area	0.017^{***} (0.006)	-0.003^{***} (0.000)
Concentration of apples	−0.032 (0.038)	0.001 (0.003)
Apple growing years	−0.002 (0.005)	0.000 (0.000)
Orchard topography	0.125^{**} (0.050)	−0.003 (0.004)
Disaster damage	0.017 (0.104)	−0.003 (0.009)
Village economy level	−0.024 (0.092)	−0.005 (0.008)
Express logistics convenience	0.066 (0.090)	−0.000 (0.008)
Ln income	0.017 (0.044)	−0.001 (0.004)
Shaanxi Province	0.728^{***} (0.094)	0.025^{***} (0.008)
Cons	−0.283 (0.623)	1.01^{***} (0.0550
Wald Chi^2		110^{***}
Observations		1167
Log-likelihood		154

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard error in parentheses (under coefficients).

the regression results. The significance and direction of the core variables are consistent with the baseline regression results.

5 Conclusions and policy implications

This study used survey data from 1167 apple growers in Shaanxi and Gansu Provinces from 2022 and uses the PSM method to examine the impact of DATES on OMF adoption behavior. The baseline regression results indicate that, following the application of unmatched and matched samples to mitigate varying selection bias issues, DATES users have higher probabilities and intensities of adoption than non-users. Concurrently, the model examines the impact mechanism of DATES, revealing that it significantly enhances OMF adoption through benefit-cognitive effects and transaction-cost effects. Heterogeneity analysis indicates that DATES has a substantial influence on farmers with higher social capital and elevated economic status. To enhance the credibility of the findings, robustness tests were conducted by substituting key variables and models, and the outcomes remained statistically significant. Nevertheless, this study had certain limitations. First, the measurement of the DATES variables must be more comprehensible. For example, the assessment of DATES-related applications and their significance can serve as additional measurement indicators. Second, the data used were cross-sectional, which may have had missing variables and it was impossible to explore the dynamic impact of DATES on OMF adoption. Subsequent research could further consider the impact of incorporating policy factors.

Several policy recommendations can be made from this research. First, it is of paramount importance to leverage rural revitalization strategies to enhance the top-level design of DATES systems. This entails the reinforcement of infrastructure development in rural areas pertaining to digital agricultural technology, dissemination of knowledge on the use of DATES, and simultaneous mitigation of challenges and entry barriers. Second, it is recommended that governments adopt a comprehensive approach that encompasses both offline and online channels. The objective of this strategy was to provide farmers with a comprehensive understanding of green production technology, thereby enhancing their awareness and fostering enthusiasm for adoption. Third, policy formulation must consider the diverse endowments of rural households because the intensity of DATES on technology adoption varies significantly based on the characteristics of individuals and families. This variability is evident in the heterogeneity observed in the technology adoption behavior of farmers with distinct social capital and economic levels. Consequently, it is imperative to acknowledge the heterogeneity in the responses of farmers with varying characteristics. Farmers with higher response levels should be targeted and guided toward actively adopting the OMF. This should be performed in a focused and biased manner to achieve the greatest possible advantages. Concurrently, efforts should be intensified to address and eliminate obstacles for farmers with less favorable responses. For those who are reluctant to adopt, strategies should be developed to address this and meticulously work toward the widespread adoption of OMF.

Supplementary materials

The online version of this article at https://doi.org/10.15302/J-FASE-2024590 contains supplementary material (Table S1).

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Compliance with ethics guidelines

Xinyi Ning, Yihan Chen, and Minjuan Zhao declare that they have no conflicts of interest or financial conflicts to disclose. All applicable institutional and national guidelines for the care and use of animals were followed.

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